A COMPREHENSIVE APPROACH TO SECURE AND EFFECTIVE FALL DETECTION IN IOT HEALTHCARE SYSTEMS

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Abstract

This thesis addresses the critical challenges at the intersection of the Internet of Things (IoT) and healthcare, focusing primarily on innovative solutions for fall detection and data privacy. The research begins by underscoring the urgent need for robust, secure fall detection systems, which sets the tone and motivation for the ensuing chapters. A comprehensive survey of the existing literature is provided, encompassing key technologies like Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) that serve as the theoretical foundation for the research. The core contribution is a novel Falls Management Framework (FMF) that employs a fusion of wearable and non-wearable sensors for effective fall detection. The framework utilizes various machine learning algorithms, with special emphasis on our proprietary Adaptive Context-aware Fall Detection Algorithm (ACFDA), optimized for minimizing false negatives and positives. In addition to FMF, the thesis explores innovative technologies in existing systems like SmartFall and FallRisk, and presents an advanced fall detection system based on visual object recognition algorithms. This latter system offers a comfortable, non-intrusive alternative to wearable sensors by using environmental sensors and real-time video analysis. Furthermore, the thesis addresses the significant issue of false detection rates and introduces privacy-preserving methods such as skeletal pose imaging and visual encryption techniques. This multi-layered approach aims to harmonize effective fall detection with individual privacy concerns. The findings and contributions of this research not only advance the field of IoT-based healthcare solutions but also promise to have immediate practical applications, especially for the vulnerable elderly population.

Contents

List of Tables

List of Figures

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the qualification of any other degree or diploma of a university or other institution of higher learning.

Signature of student

Publications

This thesis is based on the following original publications which are referred to in the number as Paper 1 - Paper 11. The publications are reproduced with kind permission from the publishers.

1. **Nguyen, H.**, Mai, T. G., Nguyen, M.(2023). A Holistic Approach to Elderly Safety: Sensor Fusion, Fall Detection, and Privacy-Preserving Techniques. *In Image and Video Technology: 11th Pacific-Rim Symposium, PSIVT 2023, Auckland, New Zealand, November 22-24, 2023. (Accepted)*
2. Le, H., Nguyen, M., Yan, W. Q., **Nguyen, H.** (2021). Augmented Reality and Machine Learning Incorporation Using YOLOv3 and ARKit. *Applied Sciences, 11*(13), 6006.
3. **Nguyen, H.**, Nguyen, M., Sun, Q. (2021). Electric scooter and its rider detection framework based on deep learning for supporting scooter-related injury emergency services. *In Geometry and Vision: First International Symposium, ISGV 2021, Auckland, New Zealand, January 28-29, 2021, Revised Selected Papers 1 (pp. 233-246). Springer International Publishing.*
4. Madanian, S., **Nguyen, H.H.**, Mirza, F. (2021). Wearable Technology. *In: Gu, D., Dupre, M.E. (eds) Encyclopedia of Gerontology and Population Aging. Springer, Cham. https://doi.org/10.1007/978-3-030-22009-9-459.*
5. **Nguyen, H.**, Nguyen, M., Nguyen, Q., Yang, S., Le, H. (2020, October). Web-based object detection and sound feedback system for visually impaired people. *In 2020 International Conference on Multimedia Analysis and Pattern Recognition (MAPR) (pp. 1-6). IEEE*
6. **Nguyen, H.** Nguyen, M., (2019, December). Fast and Secured Visual Content Hiding in Lossy Compressed Images and Video Streams. *In 2019 International Conference on Image and Vision Computing New Zealand (IVCNZ) (pp. 1-6). IEEE*
7. **Nguyen, H.**, Mirza, F., Naeem, M. A., Baig, M. M., (2019). Falls management framework for supporting an independent lifestyle for older adults: a systematic review. *Aging clinical and experimental research, 30(11), 1275-1286*

8. **Nguyen, H.**, Zhou, F., Mirza, F., Naeem, M. A. (2018, October). Fall detection using smartphones to enhance safety and security of older adults at home. *In 2018 Eleventh International Conference on Mobile Computing and Ubiquitous Network (ICMU) (pp. 1-2). IEEE*

9. **Nguyen, H.**, Mirza, F., Naeem, M. A., Baig, M. M. (2017, November). Detecting falls using a wearable accelerometer motion sensor. *In Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (pp. 422-431)*

10. Ma, J., **Nguyen, H.**, Mirza, F., Neuland, O. (2017). Two way architecture between IoT sensors and cloud computing for remote health care monitoring applications. *In Proceedings of the 2017 European Conference on Information Systems*

11. **Nguyen, H.**, Mirza, F., Naeem, M. A., Nguyen, M. (2017, April). A review on IoT healthcare monitoring applications and a vision for transforming sensor data into real-time clinical feedback. *In 2017 IEEE 21st International conference on computer supported cooperative work in design (CSCWD) (pp. 257-262). IEEE*

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Auckland, New Zealand
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Chapter 1

Introduction

1.1 Motivation

In modern society, the number of older adults who either opt or are necessitated to live independently is on the rise, posing a complex set of challenges for healthcare providers. These challenges extend beyond the potential for medical emergencies, encompassing concerns like social isolation, depression and anxiety, and inadequate nutrition.

Particularly salient among these risks is the elevated likelihood of falls, which are not only frequent in the elderly population but also have severe implications. These falls could lead to debilitating injuries, significantly affecting the quality of life and sometimes necessitating long-term institutional care. In this context, it's worth noting that many falls go undocumented, even when the individual does not have noticeable cognitive impairments (Ungar et al., 2013). Various factors contribute to the prevalence of falls among older adults—these range from age-related physiological changes to environmental hazards. Therefore, fall detection and risk assessment are critical for formulating effective prevention strategies.

As shown in Figure 1.1, these falls can have dire consequences, particularly when

Figure 1.1: Illustrations of Vulnerable Situations: Elderly Individuals Experiencing Falls When Alone
(Elliott, Painter & Hudson, 2009)

they occur in the absence of immediate help. Comprehensive, multi-factorial assessments are, therefore, indispensable in gauging the risks of falls effectively and devising targeted prevention programs.

The changing demographics worldwide, characterized by an aging population (United Nation, Department of Economic and Social Affairs, Population Division, 2015; Harper, 2006), further accentuate these challenges, leading to increased healthcare expenditures and a surge in the prevalence of chronic conditions (Thom et al., 2006; Centers for Medicare & Medicaid Services, 2015). Health monitoring is becoming an integral component of individual healthcare, especially for older adults and people with chronic illnesses, as it aims to reduce hospital visits while enhancing the overall quality of life (Dierckx, Pellicori, Cleland & Clark, 2015). Traditional models of health monitoring are becoming increasingly untenable due to their time-consuming nature and inconvenience for both healthcare providers and patients (Karthikeyan, Devi & Valarmathi, 2015). Hence, there is a pressing need for efficient healthcare solutions that not only alleviate the burden on existing systems but also contribute to better healthcare outcomes. If the current healthcare practices persist, New Zealand's government healthcare spending is projected to rise by 1.5 times from 2016 to 2060, accounting for approximately 11 percent of the GDP by 2060 (Ministry of Health, 2016).

IoT is promising for developing remote healthcare monitoring systems. IoT applications present a paradigm to connect physical and virtual things (Azimi, Rahmani, Liljeberg & Tenhunen, 2016) and enables these things to communicate, share information and coordinate decisions. In recent years, IoT-based applications in the medical field have drawn substantial attention of researchers and technologists.

Technology has come a long way in recent years, especially in terms of real-time monitoring of elderly individuals. Although there are no well-known applications specifically designed for this purpose, there is no shortage of options available to help improve the quality of life for older adults.

One of the main concerns with real-time monitoring is ensuring the security of personal identity. This is a significant challenge as sensitive data must be protected to prevent any misuse or exploitation. It's important to use appropriate encryption and security measures to keep personal data safe from any unauthorized access.

Another important feature of real-time monitoring is the ability to provide caregivers with a real-time display of the elderly person's activity. This allows caregivers to keep an eye on the individual's health and well-being, and respond promptly to any potential issues.

However, there are challenges associated with storing large amounts of data, especially when videos are recorded 24/7. This can be expensive and may not be feasible for all users. It's important to balance the need for comprehensive monitoring with the cost of maintaining and storing large amounts of data.

Overall, the goal of real-time monitoring is to help minimize the risk of severe injury for elderly individuals who live alone. With the right technology and security measures in place, it's possible to provide elderly individuals with the support they need to live independently and safely.

The use of real-time monitoring technology can play a crucial role in helping to minimize the risk of severe injury for elderly individuals who live alone. By providing caregivers with a real-time display of the individual's activity, any potential issues can be identified and addressed promptly. Additionally, the use of sensors and other monitoring devices can help to detect falls or other accidents and alert caregivers or emergency services. With the right technology and support in place, it's possible to provide elderly individuals with the safety and security they need to live independently and reduce the risk of severe injury.

1.2 Thesis Goals and Research Questions

The overarching aim of this research is to conceptualize, design, and validate a cost-effective, yet robust, system for monitoring elderly individuals living alone, with an emphasis on ensuring both their security and privacy. To achieve this objective, the study scrutinizes a plethora of Internet of Things (IoT) technologies and determines the most efficacious options for senior residences.

To fulfill these research aspirations, we pose the following key Research Questions **(RQs)**:

RQ 1: *Which technologies offer a balanced blend of efficiency and privacy for home-based elderly monitoring?*

RQ 2: *How reliable are wearable IoT devices for the precise categorization of activities, particularly in detecting falls?*

RQ 3: *What alternative non-wearable IoT devices can be employed for precise activity classification, specifically for fall detection?*

RQ 4: *How can we mitigate risks related to visual data breaches when employing RGB/IR camera systems for monitoring?*

RQ 5: *What techniques based on deep learning can be developed to improve the* *precision of human activity detection?*

RQ 6: *What strategies can be applied to minimize cloud storage requirements for real-time health monitoring data?*

The research questions presented above are of significant importance, as they address key challenges faced in the fields of computer vision, privacy, and healthcare monitoring. The elderly population is growing rapidly, and there is an increasing need for effective monitoring solutions that respect their privacy and provide accurate health data. This thesis aims to fully or partly answer these research questions by exploring suitable technologies for elderly care, evaluating the performance of wearable and non-wearable IoT devices in activity classification, examining methods to minimize visual data breaches, enhancing the accuracy of human detection using deep learning models, and proposing strategies to reduce the cloud storage requirements for real-time health monitoring data. The insights gained from addressing these questions will contribute to the development of more effective and privacy-preserving monitoring solutions for the elderly.

1.3 Contributions of Thesis

This thesis primarily revolves around the development of an innovative, robust, and privacy-preserving system for fall detection in the context of IoT-enabled healthcare. The architecture of our proposed system, as illustrated in Fig. 1.2, integrates wearable and non-wearable sensor technologies, as well as cloud-based solutions, to effectively monitor falls and ensure data privacy for the vulnerable elderly population.

In bringing this system to fruition, we make several novel contributions in both the design and operational aspects, which span client-side, server-side, and system architecture. The thesis is centered around the following major contributions:

1. **Comprehensive Survey and Theoretical Framework**: A thorough exploration

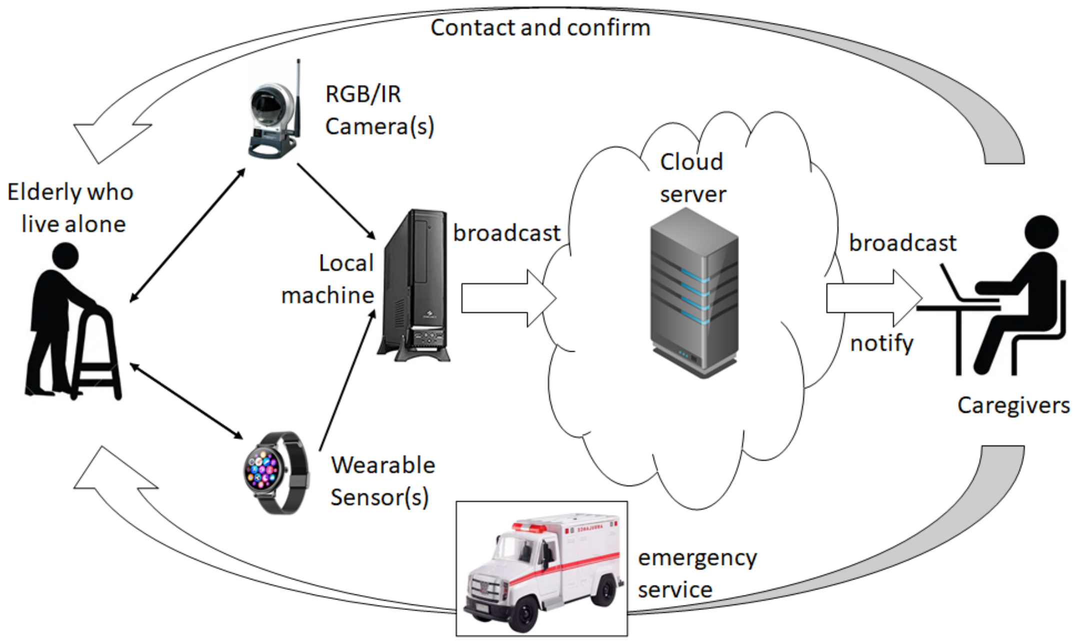


Figure 1.2: Overall Architecture of the proposed system.

of existing technologies and methodologies in IoT healthcare and fall detection. This includes discussions on Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) to lay the groundwork for subsequent chapters.

2. **Novel Falls Management Framework (FMF)**: We introduce a new framework that fuses wearable and non-wearable sensor technologies to develop a highly effective fall detection system. FMF employs machine learning algorithms like SVM, k-NN, and Naive Bayes classifiers, along with our Adaptive Context-aware Fall Detection Algorithm (ACFDA) to accurately distinguish falls from Activities of Daily Living (ADL).

3. **Visual Object-based Fall Detection Algorithm**: This system deploys environmental sensors and video analytics for fall detection, surpassing the limitations of wearable sensors. The algorithm consists of four key components: Video Capture and Playback, Pose Landmark Detection, Fall Recognition, and User Interface

Interactivity. It is extensively validated using the SysFall dataset.

4. **Privacy-Preserving Approaches**: Two innovative methods for manual verification of fall incidents are introduced—skeletal pose imaging and visual encryption. These measures provide a balance between fall detection effectiveness and individual privacy concerns. The thesis also explores image encryption techniques like steganography and reversible data hiding to bolster security and privacy.

Chapter 2

Literature Review

2.1 Introduction

The increasing trend of ageing populations all over the world in recent years (Harper, 2006) has led to complex health issues, including the increase in chronic diseases and rise in hospital and clinical services expenditures (Thom et al., 2006). Health monitoring is playing an important role in maintaining health for individuals, especially for the elderly or people with chronic diseases because it can reduce hospitalization and increase quality of life (Dierckx et al., 2015). Traditional health monitoring models are time-consuming and inconvenient for all involved (Karthikeyan et al., 2015). These models will be insufficient to meet the need of medical services in our ageing society. There has been a demand for developing efficient healthcare solutions which help to decrease the pressure on hospital systems and healthcare providers, improve the quality of care as well as have a part in reducing healthcare costs by keeping patients out of hospitals for routine care. It is expected that New Zealand's government health spending would increase 1.5 times in the period from 2016 to 2060, reaching about 11 percent of GDP in 2060, if there was no change in funding and delivering healthcare services [8].

Following are the healthcare challenges that motivate our research. Firstly, populations are ageing all over the world. According to the United Nations [1], the number of people aged 60 and over in the world reached 901 million in 2015 and it is projected to grow to 1.4 billion in 2030 and nearly 2.1 billion in 2050. It is forecasted that the largest age group will be 65+, and the average age will be approximately 50 in many countries in Asia and Europe in 2050 (Harper, 2006). Secondly, the increase in chronic diseases. In Europe, the most common diseases that affect 15 million people with an incidence of 3.6 million new cases every year are Chronic Heart Failure (CHF), Chronic Obstructive Pulmonary Disease (COPD) and Diabetes. The same trend is also recorded in U.S. (Thom et al., 2006). Thirdly, hospital and clinical services expenditures are rising. The Centers for Medicare and Medicaids Services (CMS) reported that hospital expenditures in U.S. grew from 3.5% in 2013 to 4.1% in 2014, reaching to $971.8 billion in this year [5]. Similarly, physician and clinical services expenditures increased from 2.5% in 2013 to 4.6% in 2014, reaching to $603.7 billion in 2014 [5].

Present IoT applications and case studies in the medical field are often ad-hoc, focusing on implementation and technologies at specific settings and scenarios. For example, authors in (Gund et al., 2008) focused on the implementation of a telecare system. The prototype of the system was evaluated in Sweden using a two step evaluation, including a ten-patient survey and a field trial at home with two chronic heart failure patients. The results show that the system is user friendly and easy to use, however it had limited wider integration or ongoing usage. On the other hand, clinical support algorithms exist, but are often underutilized. In (Baig & GholamHosseini, 2013), for instance, a diagnostic module is proposed using fuzzy logic to perform early diagnosis and alert for Hypertension and Hypotension however this is not widely adapted.

With the development and progress of science and technology, repetitive and time-consuming work have been taken over by the computer. Computer vision, as an inter-discipline based on image processing, machine learning and pattern recognition, is a rapidly developing research field in recent years. Object detection is a significant task in computer vision and it is used in detecting an object from certain scenes via some specific approach and algorithm (Z. Chen, Khemmar, Decoux, Atahouet & Ertaud, 2019). Machine learning raised in 1980 as one of the sub-branch of artificial intelligence. While artificial intelligence started since the 1950's, one of its subbranch machine learning become to flourish in the 1980s. Deep learning which emerged in 2010 as the hottest area in machine learning, starts to gain more and more attention to solving public society problem(Dhande, 2017). One of the common application of object detection is to detect human via deep learning model. Object detection can be achieved by deep learning technique which is able to perform end-to-end detection without specifically defining features and it is typically based on Convolutional Neural Networks (CNN).

In this chapter, a summary of IoT technologies and Deep Learning techniques are presented.

2.2 Internet of Thing

This section provides an overview of present technologies that support IoT-based applications. An IoTTA for the design and development of solutions for transforming sensor data into real-time clinical feedback in healthcare systems is proposed. The IoTTA is an architecture to situate the IoT based ubiquitous applications that may comprise multiple tiers of technology. Finally, suggest scenarios where IoTTA can be applied.

2.2.1 IoT Wearable Devices

There are a large number of Consumer Health Wearable Devices, that are listed in Fig. 2.1 (Piwek et al., 2016). They are headbands, sociometric badges, camera clips,

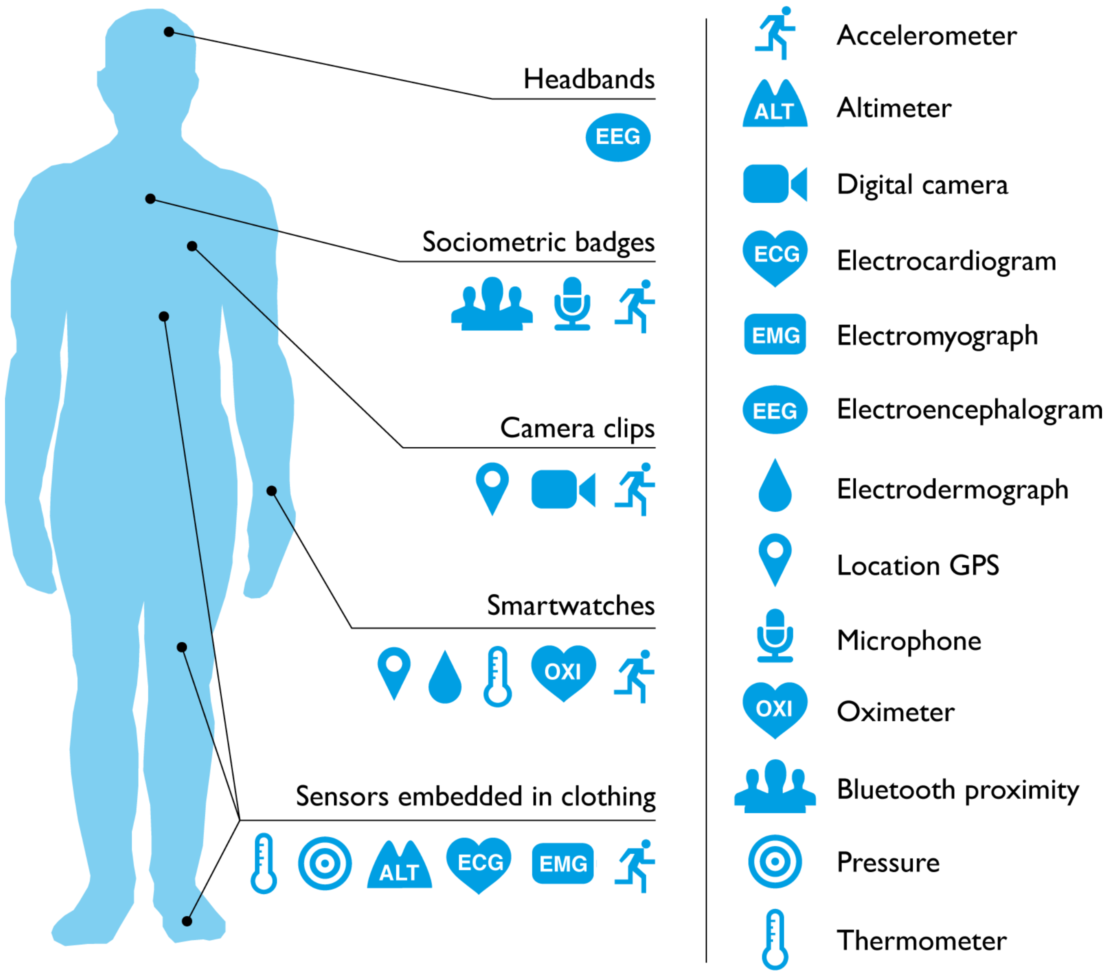


Figure 2.1: The Rise of Consumer Health Wearable Devices
(Piwek, Ellis, Andrews & Joinson, 2016)

smart watches, and other sensors embedded in clothing. Those devices could help estimate in real-time values such as:

- **Accelerometer**: An accelerometer is a device commonly used for fall detection in elderly individuals. It measures acceleration forces and can detect changes in velocity or direction of movement, which is critical in detecting falls. The device is typically worn on the wrist, hip or ankle, and uses algorithms to determine whether a sudden change in acceleration is indicative of a fall. If a fall is detected, the device can trigger an alert to caregivers or emergency services, helping to ensure that the individual receives prompt medical attention. Additionally, some accelerometers are designed to track other movements and can provide valuable information on the individual's overall activity level and mobility. As a non-invasive and relatively affordable technology, accelerometers have the potential to be a valuable tool in fall detection and prevention efforts for elderly individuals.

- **Altimeter**: An altimeter is a device that measures altitude, which can be useful in fall detection for elderly individuals. When a fall occurs, the individual's altitude changes rapidly, which can be detected by the device. Altimeters are typically incorporated into wearable devices, such as smartwatches or fitness trackers, and use algorithms to determine whether a sudden change in altitude is indicative of a fall. If a fall is detected, the device can trigger an alert to caregivers or emergency services, enabling prompt medical attention. Additionally, some altimeters can track changes in altitude over time, providing valuable information on the individual's overall mobility and activity level. While altimeters may not be as widely used for fall detection as accelerometers, they can still be a valuable tool for ensuring the safety and well-being of elderly individuals living alone.

- **Oximeter**: An oximeter is a device that measures oxygen saturation levels in the blood, which can also be used for fall detection in elderly individuals. During a fall, oxygen levels may drop due to physical exertion or stress, and an oximeter can detect these changes. Oximeters are typically worn on the finger or earlobe and use light absorption to determine oxygen saturation levels. If a fall occurs, and oxygen levels drop below a certain threshold, the device can trigger an alert to caregivers or emergency services, indicating that medical attention is needed. Additionally, oximeters can be useful in tracking the individual's overall health and wellness, providing valuable information on changes in oxygen saturation levels over time. While oximeters are not as commonly used for fall detection as accelerometers, they can still be a valuable tool in ensuring the safety and well-being of elderly individuals living alone.

2.2.2 IoT Consumer Security Cameras

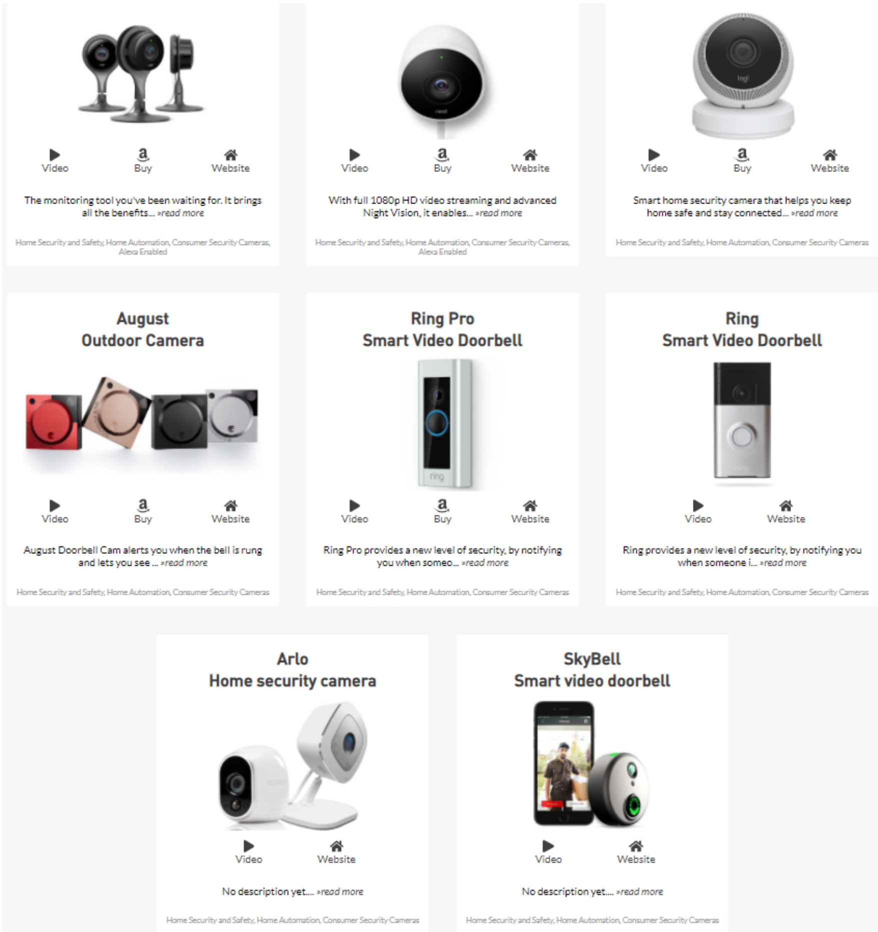


Figure 2.2: Some available IoT Consumer Security Cameras

IoT (Internet of Things) consumer security cameras have emerged as a popular technology for fall detection in elderly individuals living alone. With the rise of smart home devices and the increasing popularity of home security cameras, these devices have become an accessible and affordable option for ensuring the safety and well-being of older adults. In this article, we will explore the use of IoT consumer security cameras for fall detection and the benefits and limitations of this technology.

One of the main advantages of using IoT consumer security cameras for fall detection is that they provide a visual record of the individual's activity. By using computer vision and artificial intelligence, these cameras can detect changes in the individual's posture, gait, and movements, allowing for the detection of falls or other potential accidents. The cameras can also track the individual's activity levels, providing valuable insights into their daily routines and habits.

Another benefit of using IoT consumer security cameras for fall detection is that they can provide real-time alerts to caregivers or emergency services. When a fall is detected, the camera can trigger an alarm, sending an alert to the individual's designated contacts, such as family members or healthcare providers. This can be especially helpful in cases where the individual is unable to call for help themselves.

However, there are also limitations to using IoT consumer security cameras for fall detection. One of the main challenges is ensuring the privacy and security of personal data. With cameras constantly recording, there is a risk of sensitive information being accessed or leaked, which can be a serious concern for older adults. It's important to use appropriate encryption and security measures to protect personal data from unauthorized access.

Another limitation is the potential for false positives or false negatives. While the technology used in these cameras has improved significantly in recent years, it is not foolproof, and there is still a risk of false alarms or missed falls. This can be a particular concern for individuals with chronic conditions or disabilities, whose movements may be different from those of the general population.

Additionally, the cost of IoT consumer security cameras can be a barrier to access for some individuals. While the cost of these devices has decreased in recent years, they still require a significant upfront investment, and ongoing maintenance and monitoring can add to the overall cost.

In conclusion, IoT consumer security cameras have emerged as a valuable tool in fall detection for elderly individuals living alone. They provide a visual record of the individual's activity and can provide real-time alerts to caregivers or emergency services. However, there are also limitations to this technology, including concerns around privacy and security, potential for false positives or negatives, and cost. As with any technology, it's important to carefully consider the benefits and limitations before deciding whether to incorporate IoT consumer security cameras into a fall detection strategy for an elderly loved one.

2.2.3 IoT architecture

IoT-based applications can be implemented by integrating various technologies such as wireless communications, sensor networks, data processing, and cloud computing. The combination of these technologies in an IoT system can be represented as shown in IoTTA (Fig. 1) We present this architecture as five tiers named Sensing, Sending, Processing, Storing and Mining and Learning. The following sections outline functions and main elements of each layer.

Sensing layer

Sensing layer involves assembly of sensors or wearable devices for recording health parameters of patients. Vital signs such as: body temperature, blood pressure, pulse rate, and respiratory rate are most common parameters used (Ahmed, Banaee, Rafael-Palou & Loutfi, 2015). However, depending on application purpose, other parameters are included. For example, heart failure patients' need monitoring for following parameters: ECG, Oxygen Saturation (SpO2), heart rate, and weight [10 - 20]. Whereas blood glucose needs to be measured for diabetic patients (Chang, Chiang, Wu & Chang, 2016). In applications that support Ambient Assisted Living (AAL) for elderly people or disabled, activity monitoring will be required (Ahmed, Björkman, Čaušević, Fotouhi &

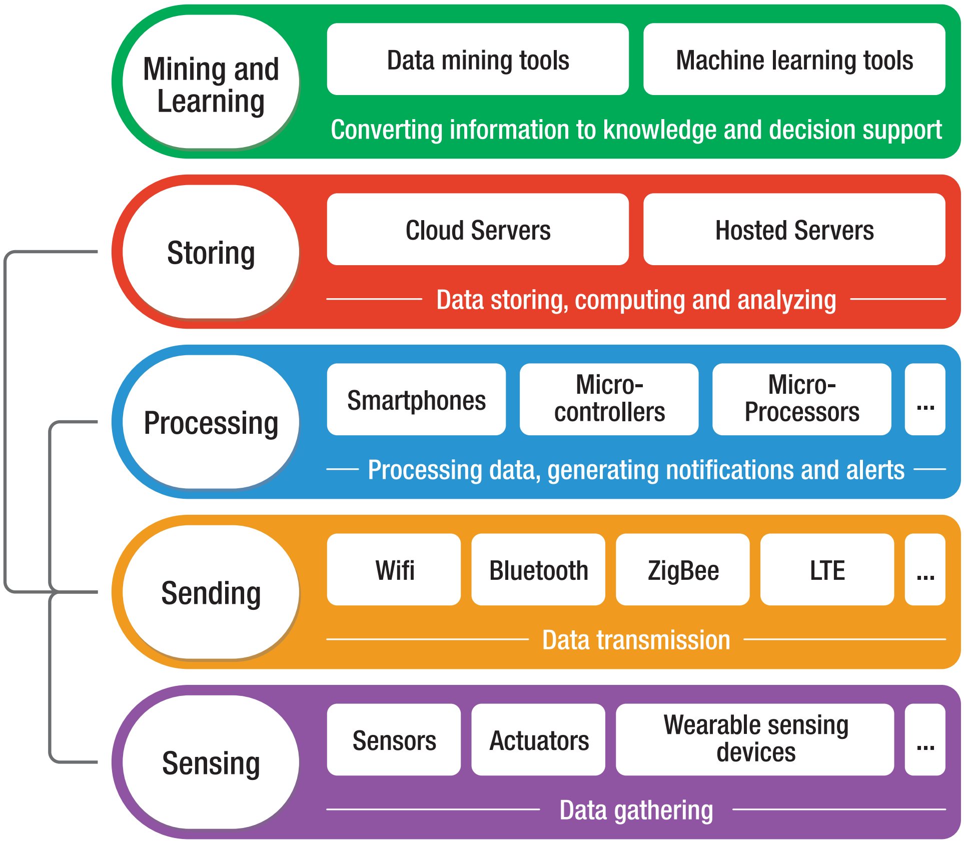


Figure 2.3: IoT Tiered Architecture (IoTTA)

Lindén, 2016). A combination of accelerometers and gyroscopes are used for gathering data in many health monitoring systems for predicting risk of falls (Chuang et al., 2015).

Sensors are regarded invasive or non-invasive sensors. Invasive techniques are more efficient than non-invasive techniques, but they may not be the right option for the elderly unless the problem is severe (Sharma et al., 2016). In some systems, actuators are used for triggering alerts (Chuang et al., 2015) or adjusting environment parameters (Basanta, Huang & Lee, 2016). Presently there has been much development in many types of intelligent sensors which can be used in IoT systems, with in turn extends the capability of IoT applications (Li, Da Xu & Zhao, 2015). Designing sensing layer of an IoT should take into consideration the following aspects: the cost, size, energy consumption of sensing devices; how to deploy and organize sensors; communication capability of sensors (Li et al., 2015).

Sending layer

Sending layer in IoTTA provides a protocol for things to connect and share data. In addition, sending layer enables data from existing IT infrastructure to be accessed (Li et al., 2015). The data communication in IoT includes local and global communication (Ahmed et al., 2016). In monitoring systems, wireless technology is used for data transmission. Wireless communication standards are helpful to ensure standardisation and compatibility in IoT health monitoring systems.

Local communication between sensing layer and processing layer, is normally implemented by Bluetooth (Suh et al., 2010, 2011; Lan et al., 2012; Bisio, Lavagetto, Marchese & Sciarrone, 2015; Chuang et al., 2015; Jimenez & Torres, 2015) or ZigBee (Zanjal & Talmale, 2016). Bluetooth is a low cost, low power consumption technology to transmit data over short distances at the frequency of 2.4GHz (Fanucci et al., 2013). ZigBee offers low power consumption, but it is not as prevalent compared to Bluetooth. Some specific communication protocols are also used including: Radio Frequency Identification (RFID) (Parida, Yang, Jheng & Kuo, 2012), Near Field Communication (NFC) and ultra-wide bandwidth (UWB) (Al-Fuqaha, Guizani, Mohammadi, Aledhari & Ayyash, 2015). RFID enables information to be exchanged between two objects - RFID tag and an RFID reader able to identify, trace and track objects within a range of 10cm to 200m (Want, 2006). NFC works at high frequency band at 13.56 MHz that allows active readers and passive tags or two active readers to communicate with data rate up to 424kbps and in the range up to 10cm (Want, 2011). UWB supports low energy, high bandwidth but short distance communications between objects (Kshetrimayum, 2009). Internet communication, is often the choice of connection between processing layer and storing layer, is established using WiFi technology or cellular networks. WiFi uses radio waves to transmit data within 100m range (Yang et al., 2015). Smart devices can communicate and exchange information via WiFi without a router (Al-Fuqaha et al., 2015). Standard wireless communications such as 3G, 4G, Long-Term Evolution (LTE) are used in many health monitoring systems (Chuang et al., 2015; Parida et al., 2012; Y. Cheng, Jiang & Shi, 2015) for data transferring between mobile phones based on GSM/UMTS network technologies. Network management technologies, network energy efficiency, quality of service, security and privacy are some issues that should be addressed in sending layer (Li et al., 2015).

Processing layer

Processing layer performs the following: firstly, aggregate data from sensing layer, secondly transfer data to storing layer, and finally process data. This layer consists of processing units and software applications that apply computational part of the application (Li et al., 2015). Processing units may be smart phones, microcontrollers, microprocessors, hardware platforms, System On Chip (SOC), Field Programmable Gate Array (FPGA). Hardware platforms such as Arduino, Phidgets, Intel Galileo, Raspberry Pi, Gadgeteer, BeagleBone, Cubieboard as well as operating systems such as Contiki, TinyOS, LiteOS, Android, and iOS have been developed recently for running IoT applications (Al-Fuqaha et al., 2015). The collected data is processed for further analysis, decision making, generating notifications and alerts.

Storing layer

IoT systems connect a large number of physical objects and generate a huge data that needs efficient storage (Al-Fuqaha et al., 2015). In IoT-based healthcare systems, the collected data from sensing layer are stored for further analysis. Many cloud platforms are available for data storage from IoT such as ThingWorx, OpenIoT, Google Cloud, Amazon, GENI (Al-Fuqaha et al., 2015). Cloud Servers and Physical Servers in storing layer have three functions including storing data, computing data and analyzing data. These functions are performed based on cloud computing technology to extract valuable knowledge and trends (Al-Fuqaha et al., 2015). With the emergence of cloud computing technologies, the burden of managing and maintaining the massive and complex medical data is shifted to the cloud, hence the efficiency and effectiveness of the health data storage and management is improved remarkably. Simultaneously, ubiquitous healthcare has been promoted by using cloud computing as a medium for e-health service delivery (Yang et al., 2015). For example, medical professionals and patients are allowed to review the health data remotely.

Mining and learning layer

Mining and learning layer involves tools that support data mining and machine learning processes. These tools are used by servers or processing units in storing layer or processing layer, respectively, for converting information to knowledge and decision support. Data mining involves discovering novel, interesting, and potentially useful patterns from large data sets and applying algorithms to the extraction of hidden information. Its functions include classification, clustering, association analysis, time series analysis, and outlier analysis (F. Chen et al., 2015). Machine learning techniques are very useful in healthcare applications as they enable managing huge databases, learn from data and improve through experience (Fang, Pouyanfar, Yang, Chen & Iyengar, 2016). Supervised learning and unsupervised learning are two types of machine learning (Yoo et al., 2012). Supervised learning (also known as predictive learning) generates prediction rules based on training data and uses these rules for predicting unseen data labels. It includes algorithms such as classification and regression. Unsupervised learning (or descriptive learning) searches the similarity between records to find the structure of unknown input data.

In the report of PWC, mobile health revenue increases from $4.5 billion in 2013 to $23 billion in 2017. In 2017, it is expected that monitoring services account for about 65% of the market, following are diagnosis services and treatment services with the percentages of the market are around 15% and 10%, respectively (Vishwanath et al., 2012). Future development can utilize IoTTA for real-time clinical feedback rather than monitoring. Furthermore, feedback should come from machine and learning layer rather than from clinicians as in current IoT healthcare applications.

2.2.4 IoT-based applications in healthcare

IoT technology is often applied to developments in remote health monitoring solutions, for those who require regular attention such as patients with chronic conditions, disabilities, and elderly. Such systems provide remote monitoring and support early detection and timely care for patients without compromising their convenience and preference of living independently outside hospital. Following is a review of IoT applications dealing with chronic patients, aged care, and emergency.

Chronic patients healthcare monitoring

Considerable research focused on developing in-home monitoring systems for patients with chronic conditions. Continuous monitoring of vital signs of patients helps to reduce re-hospitalizations by detecting anomaly early, allowing appropriate and timely interventions (Fanucci et al., 2013). Some systems measured Electrocardiography (ECG) and transmitting data to medical database via the Internet (Bai, Cheng, Lu & Huang, 2005) or wireless communications (Pollonini, Rajan, Xu, Madala & Dacso, 2012), or the collected data are used to diagnose and call emergency services if necessary (De Capua, Meduri & Morello, 2010; Jeon, Lee & Choi, 2013). Some studies tracked parameters such as blood pressure, respiration, SpO2, pulse rate, heart rate, and weight collected sensors for triggering alarms if abnormal situations are detected (Fanucci et al., 2013), or support early diagnosis of Hypertension and Hypotension (Baig & GholamHosseini, 2013).

Along with measuring vital signs, a questionnaire method is used in systems (Gund et al., 2008; Suh et al., 2011, 2010; Lan et al., 2012) to collect health status of patients. The results of the field test in Care@Distance project (Gund et al., 2008) showed that patients found the system useful, easy to use, but found the blood pressure monitor uncomfortable. Authors in (Suh et al., 2010) proposed a system for monitoring the weight, activity and blood pressure of heart failure patients, checking patients' symptoms by questionnaire and sending alerts to the healthcare provider when the collected data's values are out of the threshold range or patients develop critical symptoms. Suh et al. (Suh et al., 2011) presented a health monitoring system for CHF patients which consists of sensors, web servers, and back-end databases. Test results show that the number of weight and blood pressure reading that fell out of an acceptable range was reduced when patients were monitored by this system. The algorithms for predicting the worsening of heart failure symptoms and the predictor of daily weight changes using in health monitoring system in (Lan et al., 2012) enabled building prediction models that are up to 74% accurate, which is more than 20% higher than using daily weight change alone. Bisio et al. (Bisio et al., 2015) designed a tele monitoring platform based on smartphone for detecting activities of heart failure patients. In this platform, the smartphone is used as both a hub and a sensing, processing and transmitting device.

Aged care monitoring

Telecare applications empower individuals, especially the old aged to live more safely and more independently in their own homes (Fanucci et al., 2013). The daily needs of the elderly can be supported by technology interventions such as smart home or telemedicine (Sharma et al., 2016). Chuang et al. (Chuang et al., 2015) proposed a system called SilverLink which uses object and human sensors for indicating user activities or health status. Data collected from sensors are processed to detect abnormalities in the movement patterns. When a shift in pattern is detected, the system stimulates notifications/alerts to the emergency response team. Internal tests of the prototype conducted in Taiwan and showed that the pass rate of sensors was 70%-80%, while pass rate of human sensors was less than 60% (pass rate is defined by the number of times the system recorded the event divided by the actual number of events).

Authors in (Basanta et al., 2016) developed a Help to You (H2U) healthcare system to enhance the quality of healthcare services for the elderly. This system makes use of various technologies including wearable devices, biosensors, wireless sensor networks to support real-time activity and monitor the health status for seniors. Applications of the proposed system include emergency calls, medication reminders and symptom checks. An IoT-aware healthcare monitoring system was designed and implemented in (Jimenez & Torres, 2015) to send alerts to patient's caregivers or doctors in real time when an elderly person needs medical attention or hospitalization. Alerts' rules were configurable during runtime and the solution supported adding new sensors without interrupting the system.

Medical adherence is a challenge amongst aged patients, some studies focused on reminding patients of their scheduled medications and updating new medicine data of patients (Zanjal & Talmale, 2016). Parida et al. (Parida et al., 2012) proposed a drug management system based on RFID technology which uses RFID reader and camera to track patients' medicine usage. Intelligent pill box was presented in (Huang, Chang, Jhu & Chen, 2014) to remind patients to take medication on time. These solutions are useful for elderly people who have high risk of suffering from dementia.

Emergency applications

Emergency applications involving IoT detect abnormalities at the right time so that emergency services can be alerted (Darshan & Anandakumar, 2015). A model to do this involves monitoring patient health by medical devices, thereafter personal mobile devices analyze the collected data to identify emergency cases and transfer data to medical information systems. When a definite emergency case is detected, the ambulatory team can reach out the patient, consequently the hospital prepares for the clinical treatment, and the medical personnel send situation-aware instructions for providing first aid.

Authors in (Namahoot, Brückner & Nuntawong, 2015) presented a healthcare system consisting telemedicine diagnosis and emergency telecare. Telemedicine diagnosis provides the user with information on diseases, medical information, and treatments; while emergency telecare shows user location, emergency information, and instructions to help the users. Korzun et al. (Korzun, Borodin, Timofeev, Paramonov & Balandin, 2015) introduced reference scenarios of digital assistance services for emergency situations.

Fall prevention and fall detection are emergency applications because falls are serious health problems with older adults. Fall detection can be classified into three types: wearable device based, ambient sensor based, and vision based (Liu & Lockhart, 2014). Cheng et al. (Y. Cheng et al., 2015) proposed a real-time fall detection system based on wearable sensors to detect the motion and location of the body. The proposed system was tested with 15 activities including 10 intentional falls and 5 activities of daily lives. Each activity was performed 30 times. Test results showed that the proposed fall detection algorithm achieves an overall accuracy of 96.4%. Another solution uses the Microsoft Kinect depth sensor (Gasparrini, Cippitelli, Spinsante & Gambi, 2014) for tracking the movement of the human objects in the depth frames, and detects if a fall occurs.

2.2.5 Opportunities of IoT in healthcare

Based on our review on recent IoT applications in health applications, we can categorize the growth of IoT applications for healthcare is in areas of 1) Self Care and 2) Data

Mining and Machine Learning.

Self-care

Effective self-care among individuals seems to be one of the most difficult tasks that clinicians are facing today (Moser et al., 2012). For instance, heart failure patients can be traced to failed self-care because of the two most common reasons including nonadherence to medications and diet as well as failure to seek timely medical care for escalating symptoms (Moser et al., 2012). Authors in (Dickson & Riegel, 2009) suggested that promoting self-care abilities should go beyond the knowledge about their disease but also the skills needed for monitoring along with their signs and symptoms. Future healthcare systems with real-time clinical feedback using IoTTA can potentially deliver step-by-step instructions to patients about how to measure their vital signs, how to use their medicine, as well as giving recommendations about how to keep their parameters in normal ranges. These will be promising and cost-effective solutions for improving self-care for the elderly. In addition, personalization of health solutions by adapting to the individual's characteristic plays an important role in improving quality of care (Heijden, Velikova & Lucas, 2015).

Data mining and machine learning

Clinical support applications are usually based on comparing collected data with patients' normal ranges and generating alerts if an abnormal situation is detected. Creating notifications should be the last resort in clinical support applications because this mechanism may place a great burden on emergency systems in case of false alarms. Other methods such as using questionnaires should be performed after detecting an abnormal value in the monitored parameter for reducing false alerts. On the other hand, current IoT healthcare applications can be further developed by using data mining tools and machine learning tools to provide clinical decision support that can assist patients effectively. Predicting changes along with decision support will lessen involvement of clinicians. Feedback such as recommendations about medicine, healthy eating and exercising can be given to personal patients without clinician's intervention.

2.3 Deep Learning

Deep learning has emerged as a pivotal area of research in recent years, attracting considerable attention from scholars across various domains. This paradigm shift has given rise to an array of sophisticated algorithms aimed at target detection. Unlike traditional methodologies, deep learning algorithms demand vast datasets for training but offer the advantage of auto-encoding variances in data, thereby enhancing their representational fidelity. Intriguingly, the layered feature extraction process in Convolutional Neural Networks (CNNs) bears resemblance to the human visual mechanism—translating basic edges to intricate parts and eventually to a holistic understanding of the visual input (LeCun, Bengio & Hinton, 2015).

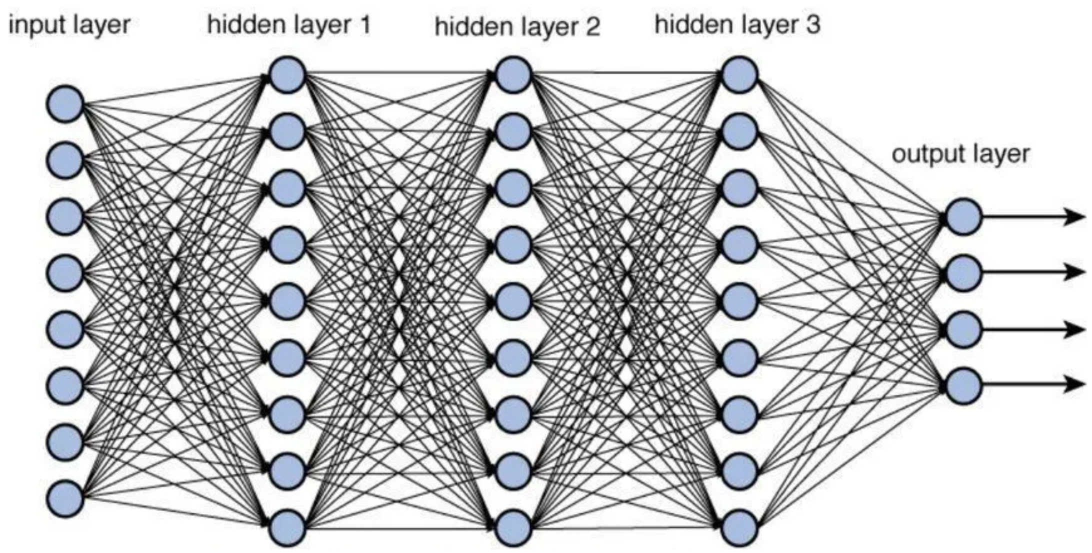


Figure 2.4: Multi-layered Architecture of a Deep Neural Network
(Parmar, 2018)

As illustrated in Figure 2.4, a deep neural network is composed of multiple layers designed for intricate feature extraction and data representation. This architectural complexity has enabled deep learning-based target detection algorithms to outperform traditional techniques, especially in real-time applications. These advancements have been further propelled by the continuous expansion of accessible data and rapid hardware innovations. Consequently, deep learning technologies are receiving burgeoning recognition and adoption across various industries worldwide.

2.3.1 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have emerged as a specialized subset of deep learning models, demonstrating unparalleled efficacy in visual tasks such as image and video processing (Krizhevsky, Sutskever & Hinton, 2012). These networks utilize a sequence of convolutional layers to autonomously identify and encode spatial feature hierarchies, which makes them exceptionally proficient at human detection and activity recognition tasks.

As seen in Figure 2.5, a typical CNN comprises multiple layers, including convolutional layers, hidden layers, and others, that work in tandem to perform complex feature extraction and representation. These layers collaborate to form a hierarchical understanding of input data, thereby making CNNs a pivotal technology for tasks requiring nuanced spatial understanding.

When it comes to tackling research question 5 (RQ 5), a multitude of CNN architectures can be investigated to enhance the accuracy of human detection mechanisms within systems designed for monitoring the elderly. Notable architectures worth exploring include VGG (Simonyan & Zisserman, 2015), ResNet (He, Zhang, Ren & Sun, 2016), and EfficientNet (Tan & Le, 2019), each offering unique advantages in improving the robustness and accuracy of elderly care monitoring systems.

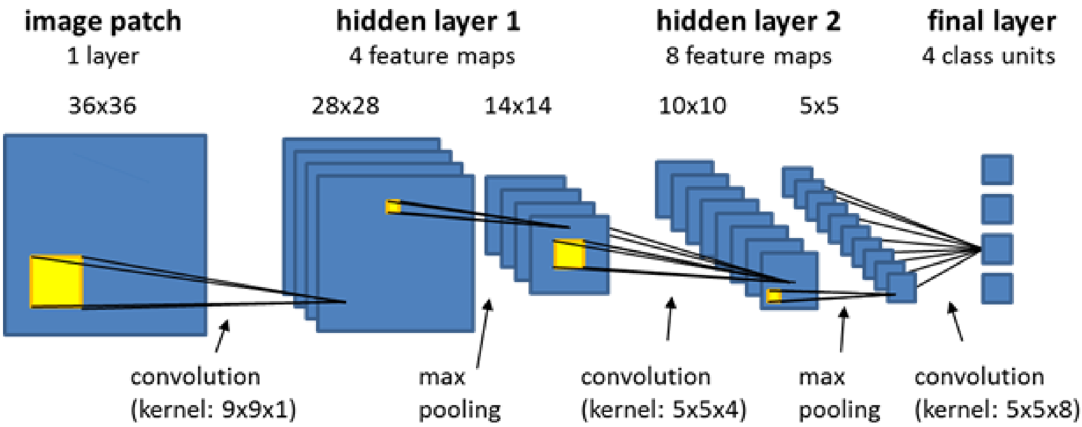


Figure 2.5: Detailed View of a Convolutional Neural Network with Dual Hidden Layers (Sewak, Karim & Pujari, 2018)

2.3.2 Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) specifically designed to model temporal dependencies in data (Hochreiter & Schmidhuber, 1997). They are particularly useful for analyzing time-series data, such as the sensor readings from wearable IoT devices (RQ 2) or the video frames captured by cameras (RQ 3). LSTMs can be employed to improve the activity classification and fall detection performance of the monitoring system, as they can effectively capture the temporal dynamics of human movements.

2.3.3 Data Augmentation

Data augmentation techniques can help improve the performance of deep learning models by artificially increasing the amount and diversity of training data (Shorten & Khoshgoftaar, 2019). This can be particularly beneficial for addressing RQ 5, as a larger and more diverse dataset can enable the model to better generalize to new and unseen data. Common data augmentation techniques for image data include rotation, flipping, scaling, and color jittering, while for time-series data, techniques such as time warping, time slicing, and random sampling can be employed.

2.3.4 Model Compression and Optimization

To minimize the required cloud storage for storing real-time health monitoring data (RQ 6), model compression and optimization techniques can be explored. These techniques aim to reduce the size and computational complexity of deep learning models without significantly affecting their performance (Y. Cheng, Wang & Zhou, 2017). Some popular approaches include weight quantization, pruning, knowledge distillation, and network architecture search. Implementing these methods can help reduce the storage and computational requirements of the monitoring system, making it more efficient and cost-effective.

2.4 Chapter Summary

This chapter has illuminated the increasing healthcare demands driven by an ageing global population, coupled with the rise in chronic diseases. The financial and human cost implications for healthcare providers are substantial and necessitate innovative, efficient, and cost-effective solutions.

We explored how the realm of Internet of Things (IoT) offers transformative potential for healthcare. Notably, its integration with deep learning has gained significant traction, particularly in public health issue resolution. Technologies such as Convolutional Neural Networks (CNNs) and IoT-driven architectures like IoTTA have been proposed for real-time clinical feedback systems, leveraging sensor data for fall detection, health monitoring, and disease prediction.

There is also an emergent trend of integrating technologies such as wireless communications, sensor networks, data processing, and cloud computing to develop effective IoT-based health applications. The ability of these technologies to provide automated, real-time feedback and diagnostics serves to alleviate some of the strain on healthcare providers.

These IoT applications also offer an unprecedented ability for self-care, delivering step-by-step instructions to patients, and providing crucial real-time data to healthcare providers for immediate response. Furthermore, the rise of machine learning and data mining technologies present possibilities for enhanced decision-making support, offering the potential to augment current healthcare practices significantly.

However, while these technologies show promise, it is crucial to acknowledge the associated challenges. These include issues of cost, maintenance, potential false alarms, missed falls, and the overall effectiveness and reliability of the technology.

As we move forward, it's essential to further explore various deep learning architectures and data augmentation techniques, to increase the accuracy and reliability of these systems. This could help push the envelope of IoT applications in healthcare, fostering a future where chronic disease management, patient monitoring, and preventive care are seamlessly integrated into our daily lives, fundamentally reshaping our healthcare systems for the better.

Chapter 3

Methodology

3.1 Research Methodology

The research methodology employed in this study is adapted from the multi-methodological approach for information systems research (Nunamaker Jr, Chen & Purdin, 1990). This approach is visually represented in Figure 3.1, which delineates the four key research strategies used: observation, theory building, systems development, and experimentation.

The *Theory Building* strategy involves the formulation of new concepts, ideas, and frameworks, as well as the development of novel methods or models. Outputs generated from this strategy can facilitate hypothesis generation, guide experimental design, and aid in the conduct of observations. *Experimentation* encompasses a range of investigative approaches, such as laboratory experiments, field experiments, and computer simulations. The outcomes of these experiments serve to validate or refine theories, while also contributing to system enhancements. *Observation* employs methodologies like case studies, field studies, and sample surveys to guide the crafting of specific hypotheses for experimental validation. Finally, *Systems Development* involves stages like concept design, architecture planning, prototype creation, product development,

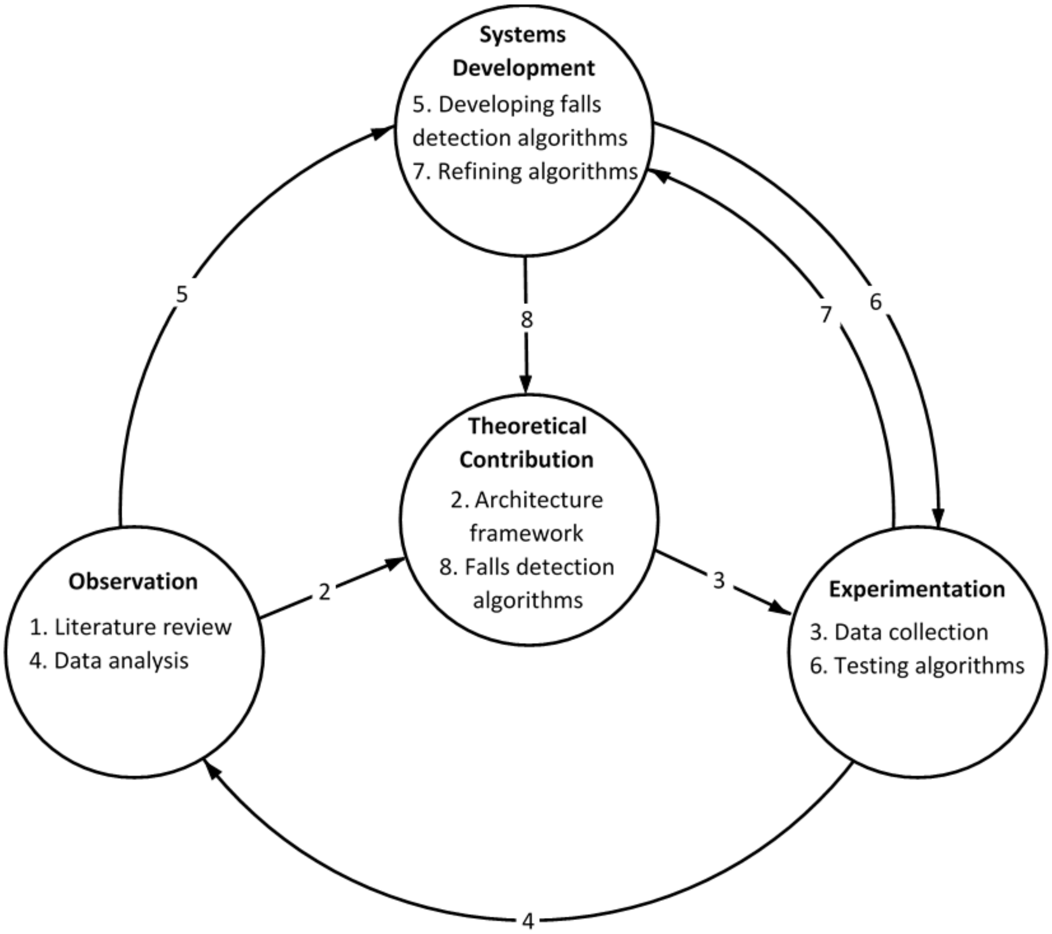


Figure 3.1: Schematic Overview of the Adapted Multi-Methodological Approach Used in This Study

and technology transfer.

As indicated in Figure 3.1, this study is structured around eight principal research activities, executed in a sequence represented by the numbered arrows. The investigation commences with a *Literature Review*, focusing on existing healthcare monitoring solutions based on the Internet of Things (IoT). The review also narrows down to the specific domain of fall management, examining sensing techniques, fall detection algorithms, and management strategies. Subsequent activities will include the development and validation of fall detection algorithms based on motion and visual object monitoring. Both public datasets and real-world data will be used for algorithm validation. Iterative phases of *Data Collection*, *Data Analysis*, *Developing Fall Detection Algorithms*, *Testing Algorithms*, and *Refining Algorithms* will be carried out to optimize the effectiveness of the developed algorithms.

3.2 Proposed Falls Management Framework

3.2.1 Overview of the Falls Management Framework (FMF)

Arising from an exhaustive review of existing fall detection studies, we introduce a comprehensive Falls Management Framework (FMF) tailored for in-home care of the elderly, as visualized in Figure 4.1. The FMF comprises key activities such as Initial Assessment (or Re-assessment), Real-time Monitoring, Fall Risk Detection, Fall Detection, On-going Support, and Response Strategy. This section elucidates the functionalities and core components of these activities.

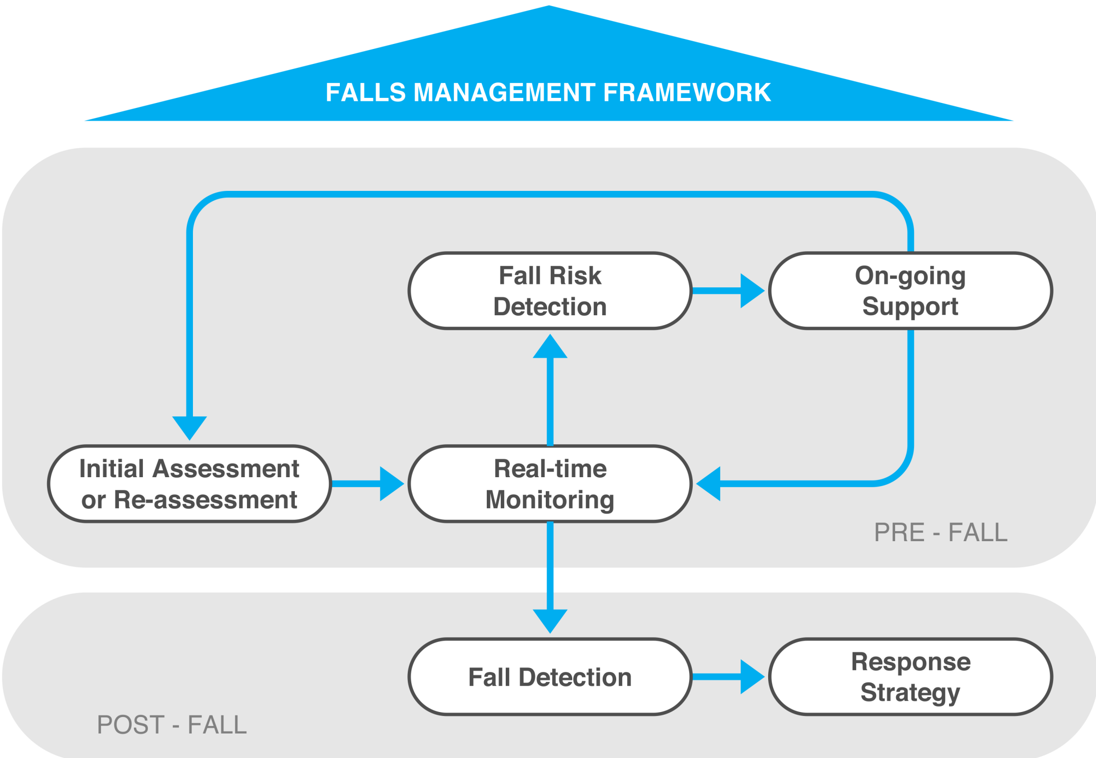


Figure 3.2: Schematic Representation of the Falls Management Framework (FMF)

Initial Assessment and Re-assessment

The initial point of engagement in the FMF is the *Initial Assessment*, conducted by healthcare professionals, as depicted in Figure 4.1. It involves a personalized evaluation encompassing the individual's fall history, mobility issues, medication, and overall physical and mental health. This information guides the selection of appropriate sensing technology. Periodic *Re-assessments* are conducted to adapt to any changes in the user's condition.

Real-time Monitoring

As the subsequent activity in FMF, *Real-time Monitoring* employs multiple sensor types for continuous observation of both the patient's vitals and environmental conditions. Sensor classifications include motion-based and environment-based, each with its own advantages and limitations.

Fall Risk Detection

Fall Risk Detection functions alongside *Real-time Monitoring* to identify potential fall hazards. Risks are categorized as intrinsic or extrinsic, with the former being physiological changes due to aging, and the latter being environmental factors like poor lighting or wet floors (Hamm, Money, Atwal & Paraskevopoulos, 2016).

On-going Support

Once a fall risk is identified, *On-going Support* provides preventive measures. Interventions may include educational programs, physical activities designed to improve mobility, or automated warnings based on sensor data (Kannus, Sievänen, Palvanen, Järvinen & Parkkari, 2005; Horta, Lopes & Rodrigues, 2015; De Backere et al., 2015).

Fall Detection

Fall Detection utilizes sensor data to discern high-risk events. Algorithms for fall detection are primarily either threshold-based or machine learning-based, each with its own sets of advantages and trade-offs (Horta et al., 2015; De Luca, Carnuccio, Garcia & Barillaro, 2016; Majumder, Saxena & Ahamed, 2016; Y. Wang, Wu & Ni, 2016).

Response Strategy

Following a detected fall, the *Response Strategy* activates, typically notifying caregivers or family members (A. L. Cheng, Georgoulas & Bock, 2016; Kau & Chen, 2015; X. Wang & Qin, 2016; Qu, Lin & Xu, 2016).

3.2.2 Insights and Future Directions

The Falls Management Framework (FMF), detailed in Figure 4.1, encompasses a comprehensive range of activities typically incorporated in current fall detection and management systems. Upon close examination, it is evident that a majority of these systems are more oriented towards post-fall interventions. This reveals a significant gap in the existing research and technology, as not enough focus is given to pre-fall preventive measures.

Strengths and Weaknesses

One of the major strengths of existing approaches is the increasing accuracy in fall detection, especially with the integration of machine learning algorithms. However, the weakness lies in the limited attention paid to preventive mechanisms and the user's quality of life. Systems often ignore the psychological and social aspects that accompany the risk and occurrence of falls. Furthermore, the sustainability and long-term effectiveness of these systems are seldom studied.

The Role of User-Centered Design

A potential avenue for improvement lies in user-centered design. Future research could benefit from a design approach that takes into account not only the technical aspects but also the user's comfort, acceptance, and psychological well-being. This would likely increase the effectiveness and user adoption rates for fall management systems.

Technological Advancements

As technology evolves, the introduction of more non-intrusive sensors and IoT devices will likely make real-time monitoring more efficient and less cumbersome for the elderly. Innovations such as smart flooring and ambient sensors could offer non-intrusive methods for both monitoring and prevention.

Prevention-Oriented Solutions

Given the current research gap in pre-fall interventions, it would be worthwhile to focus on technologies that actively engage the user in fall prevention. This could include systems that offer real-time feedback or gamified experiences that encourage the elderly to engage in balance-improving exercises and activities.

Policy and Standardization

Finally, with the growing prevalence of fall management systems, there is an urgent need for standardization to ensure that they meet minimum safety and effectiveness criteria. Policy guidelines and standardized testing methods could provide a structured approach for evaluating and implementing these technologies.

In the sections that follow, we will delve into a detailed discussion of the strengths and weaknesses of the studies reviewed, and propose a multi-faceted strategy to bolster both pre-fall and post-fall interventions.

3.2.3 Roadmap of Falls Management

Table 3.1 summarizes strengths and weaknesses of the two groups: pre-fall applications and post-fall applications. From table 1, it is clearly seen that both pre-fall and post-fall applications are not developed effectively. Some systems provide fall risk detection, however no intervention is given after a fall risk is detected (Majumder et al., 2016; Shen, Yang, Shen & Chen, 2016). Simultaneously, current post-fall intervention is sending alarm to the user's caregivers or medical team. This strategy may place a burden on healthcare services in case of false alarms. In addition, it may take long time to reach the patients if they live in rural or remote area.

The result of the review conducted by the paper indicates that the following strategies should be applied in order to achieve a sustainable falls management, avoid fall risks, and eliminate consequences in case of detecting falls.

Pre-fall strategies

Pre-fall strategies relates to interventions that help to prevent users from falling. Concept of pre-fall strategies will involve fusion of sensors, technologies and systems along with clinical assessments to create an environment where real-time data are analyzed. Applying IoTTA approach (Nguyen et al. 2017) in designing falls management systems will help to explore a range of aspects including sensing, sending, processing, storing, and mining and learning techniques for transforming sensor data into real-time clinical feedback that can assist patients to avoid falls effectively, hence lessen involvement of clinicians.

Falls can be prevented based on detecting fall risk with precision and providing appropriate and timely interventions. Few studies focus on fall risk detecting based on patient's health monitoring, except in the research conducted by (Horta et al., 2015). In this research, the monitored ECG waves are used to identify anomalies in the patient's

Table 3.1: Strengths and weaknesses of the reviewed studies

Application Type	Strengths	Weaknesses
Pre-fall	- Accurate fall risk assessment (De Backere et al., 2015). - Timely notifications (De Backere et al., 2015). - High classification accuracy for gait patterns (Majumder et al., 2016). - Successful predictions, body-independent (Shen et al., 2016). - Risk reduction instructions (Horta et al., 2015). - Robust data processing (Horta et al., 2015).	- No risk reduction guidance (De Backere et al., 2015). - No post-fall interventions (Majumder et al., 2016). - Cannot detect all falls (Horta et al., 2015).
Post-fall	- High accuracy and sensitivity (Pierleoni et al., 2015). - Energy efficiency (Gia et al., 2016). - Low complexity detection algorithms (Qu et al., 2016). - User-friendly interface (Yildirim, Ucar, Keskin & Kavak, 2016).	- Limited post-fall actions; mainly notifications.

rhythm. The system sends an alert to the user's caregiver if both a fall and an anomaly are detected. Integrating vital signs monitoring into falls management systems empowers these systems to achieve a considerable advantage in fall risk identification, detection and classification (Baig, Gholamhosseini & Connolly, 2016). For instance, a reduction of blood pressure may cause a fall (Naschitz & Rosner, 2007). Therefore, vital signs monitoring based on sensors should be further utilized in falls management systems. In order to identify intrinsic fall risk factors more efficiently, information about the patient's fall history and medication conditions need to be effectively analyzed (Baig et al., 2016).

Falls prevention strategies including post-fall review, education for both patients and staff, footwear advice, and toileting is introduced by (Oliver, 2008), however, his research only mentions about using these strategies in hospital environments. Applying these interventions in home environments may have significant contribution in supporting falls prevention. For example, falls prevention education sessions which are activity checklists including clutter reduction, furniture organization, rug, flooring and spills position, lighting, and staircase and bathroom safety are suggested in the research conducted by (Bell et al., 2011). Additionally, solutions that engage effective self-care among the elderly need to be considered, such as activities to increase adherence rates of exercise programmes (Chao, Scherer, Wu, Lucke & Montgomery, 2013) or a balance training game (Pisan, Marin & Navarro, 2013).

Post-fall strategies

Post-fall strategies relate to interventions provided after a fall is detected. Providing appropriate and timely interventions after detecting falls is extremely important, because these interventions at the earlier stages may help to mitigate the consequences after falling. The most popular response strategy used in current falls detection systems is alerting users' caregivers or clinicians for medical assistance. However, this action is costly, and it may place a great burden on emergency systems, especially in case of not injured falls or false positives. In addition, if the patient lives in rural or remote area, it may take long time to reach the patient's location. Therefore, other methods need to be utilized before using the last resort which is calling medical emergency service.

Concept of post-fall strategies should integrate neighbors in the medical emergency team because neighbors are closest to the patients, hence they would be the quickest responder if a fall is detected. This proposed strategy is described as follow: In case of detecting a fall, based on the collected data via monitoring, the system assesses how serious the fall is. If it is extremely emergency, the system send alarm directly to medical emergency service. Otherwise, notification is sent to their neighbors. When receiving notification, their neighbors reach and assist the patient. If the system receives neighbors' response indicated that the emergency situation has been resolved, it terminates the supporting activity. Otherwise, the system sends alert to medical emergency service and provides first aid instructions for neighbors to support the patient until the emergency service comes. This neighbors-assist strategy may help to reduce both response time and service costs. Moreover, it might make the patients feel more confident and mitigate the long lie situation after falling.

3.3 Breakdown of the Proposed Fall Detection Process

To cater to the needs of the elderly living alone, we propose the integration of two categories of sensors: wearable and non-wearable.

3.3.1 Wearable Sensors

Wearable sensors, such as smartwatches or adhesive body devices, primarily utilize vibrations to detect falls. However, several limitations accompany their use. First, continuous wear might lead to discomfort for the user. Moreover, the battery life and connectivity restrictions mean that users might occasionally neglect to wear these devices, thus compromising the reliability of this method. Despite these challenges, wearable sensors offer a distinct advantage in terms of user privacy, as they inherently preserve the anonymity of the data. This makes the transmission and storage of such data over the internet more secure. A detailed discussion on fall detection using these devices can be found in Chapter 4.

3.3.2 Non-wearable Sensors

Non-wearable sensors predominantly encompass cameras strategically positioned throughout the living quarters of the elderly, thereby offering continuous monitoring. These video feeds are processed online, employing advanced computer vision and artificial intelligence techniques to identify potential falls. The intricacies of this implementation are explored in Chapter 5, which focuses on Visual Object-based Fall Detection.

The primary concern with this approach lies in the risk of data breaches, potentially leading to the unauthorized dissemination of video footage. To mitigate this, we introduce two strategies for Visual Content Hiding, ensuring that the users' images remain confidential:

1. Transforming human images into skeletal or pose representations before uploading, thus anonymizing the visual content.

2. Employing a public-private key mechanism to visually encrypt the images prior to online transmission. Only authorized entities possessing the requisite keys can revert these images to their original form.

To further enhance security, these methods can be amalgamated, offering a robust system against potential leaks. This multifaceted approach to content protection is elaborated upon in Chapter 6.

Lastly, it is pertinent to note that our fall detection process is semi-automated, thus ensuring reliable identification of falls among the elderly living alone.

3.4 Chapter Summary

This chapter presented an exhaustive exploration of a multi-methodological research approach targeted at IoT-based fall management solutions within the healthcare sector.

Our approach encompassed a variety of research strategies: observation, theory-building, system development, and experimentation.

A significant portion of this chapter delineated the intricate facets of the proposed Falls Management Framework (FMF). This comprehensive framework encapsulates a series of activities: Initial Assessment, Real-Time Monitoring using both wearable and non-wearable sensors, Fall Risk Detection, Fall Detection using computer vision and artificial intelligence, On-going Support, and a comprehensive Response Strategy. Our holistic FMF not only addresses the post-fall response but also aims to preemptively mitigate fall risks.

In addition to elucidating our framework, we provided an in-depth review of existing IoT-based fall management literature. This review aimed to discern strengths, weaknesses, and noticeable gaps in current methodologies. A significant observation was the undue emphasis on post-fall interventions in many applications, often overshadowing crucial pre-fall strategies.

We have meticulously unpacked two paramount intervention categories: pre-fall and post-fall strategies. The former leans into preempting falls by synergizing sensors, advanced technologies, and clinical insights for real-time data analytics. The latter, conversely, centers on dispensing an immediate and apt response post a detected fall, also emphasizing the importance of data protection and privacy when using non-wearable sensors.

Future endeavors in this domain should concentrate on addressing the identified gaps, particularly accentuating the pre-fall phase. A more holistic approach might integrate both intrinsic and extrinsic risk factors, encompass vital signs monitoring, and incorporate a patient's historical fall data and medication profile for more nuanced fall risk assessments. Additionally, involving nearby residents or neighbors in emergency response mechanisms might offer a novel avenue for swift post-fall interventions.

In summation, the methodologies and frameworks delineated in this chapter bear immense promise for sculpting improved fall management systems in healthcare. They beckon a future where the elderly can reside in safer, more secure environments with the confidence that timely interventions are always within reach.

Chapter 4

Wearable Sensor-based Fall Detection

4.1 Introduction

In this chapter, we delve into fall detection systems that are based on wearable sensors. These systems leverage diverse data types—including acceleration signals, images, and pressure signals—captured by sensors for analysis. Employing machine learning algorithms and pattern recognition techniques, these systems aim to accurately distinguish between falls and normal activities of daily living (ADLs), thus minimizing false alarms. Such advancements hold the promise of significantly improving the safety and independence of individuals at high risk of falling, including the elderly and those with mobility challenges.

The process of data analysis and algorithm development for these systems necessitates a nuanced approach that takes multiple factors into account. Critical to the system's efficacy is the selection of appropriate features and thresholds for the fall detection algorithms, ensuring both high sensitivity and specificity. Moreover, rigorous performance testing in real-world scenarios is indispensable for validating the algorithm's reliability and effectiveness.

As depicted in Figure 4.1, flexible electronics have started to play an increasingly

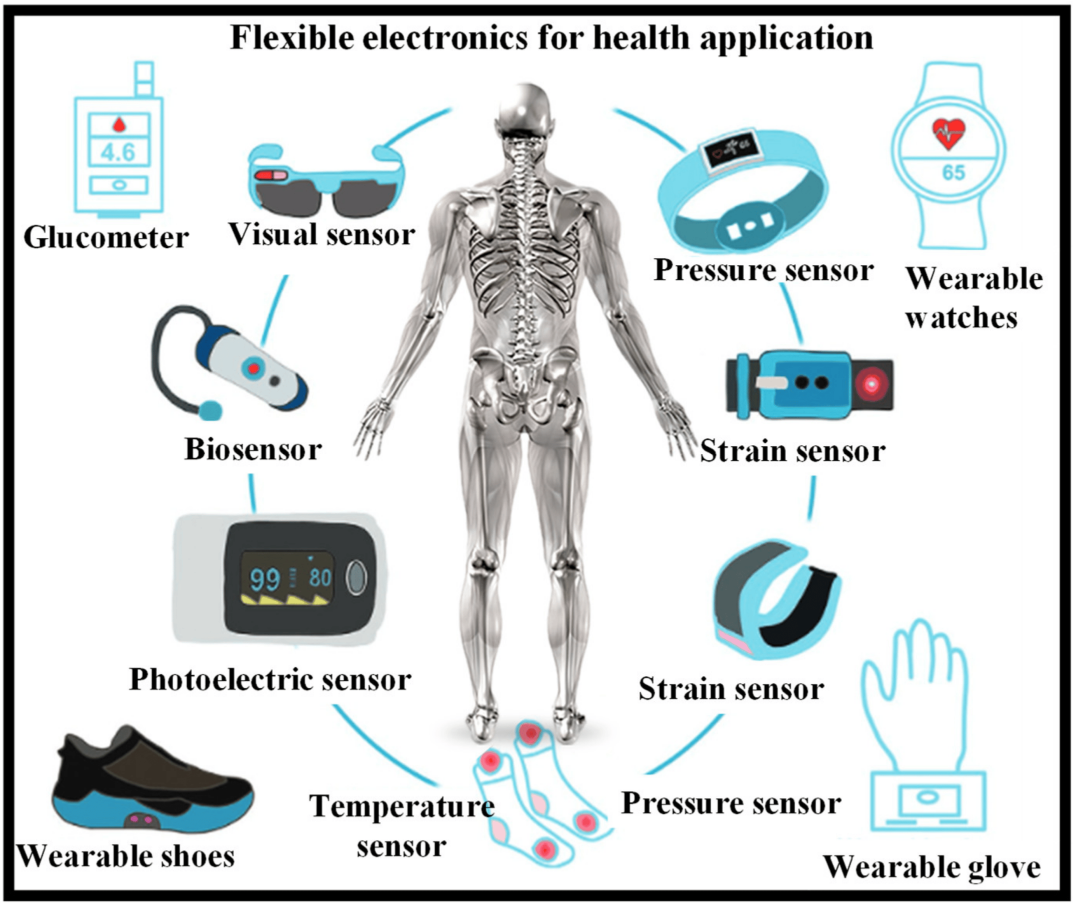


Figure 4.1: Schematic of Flexible Electronics in Personal Healthcare Applications (Butt, Kazanskiy & Khonina, 2022)

important role in personal healthcare (Butt et al., 2022), including in the design of wearable sensors for fall detection.

This chapter is organized as follows: First, we will survey existing literature to provide a comprehensive view of the state-of-the-art in wearable sensor-based fall detection. Following this, we introduce our proposed Acceleration Change-based Fall Detection Algorithm (ACFDA). A series of experiments designed to evaluate ACFDA's performance, featuring simulations involving both falls and ADLs, will be discussed. Data from these experiments serve to assess ACFDA's effectiveness in real-world conditions.

Lastly, we will outline future directions in this field, particularly the integration of fall detection systems with other technologies for a more holistic approach to fall prevention and intervention. We will conclude with a synthesis of the key findings of this research and their implications for the broader field of wearable sensor-based fall detection.

4.2 Related Work

In recent years, there has been a significant surge in research and development of fall detection systems, capturing the attention of scientists and engineers alike. These systems are designed to distinguish between falls and Activities of Daily Living (ADL) by processing and classifying various types of data, such as acceleration signals, images, and pressure signals, collected by sensors (Igual, Medrano & Plaza, 2013).

Fall detection systems can be grouped into three categories based on the devices used: ambient device-based systems, camera-based systems, and wearable device-based systems. Ambient devices like pressure sensors, PIR sensors, Doppler radars, and microphones are employed in the first category, offering cost-effective and non-invasive solutions. However, their accuracy may be affected by environmental factors (Vallabh, Malekian, Ye & Bogatinoska, 2016). The second category relies on cameras to track user movements and detect falls by identifying extended periods of inactivity. While less invasive, privacy and spatial coverage remain key challenges for this approach.

The third category, wearable device-based systems, often utilize accelerometers and/or gyroscopes to monitor user motion and differentiate falls from normal activities. These portable, affordable, and user-friendly devices can be smartphones or other gadgets like watches, belts, or waist-mounted devices, equipped with motion sensors for detecting body posture and movement. Accelerometers are the most common type of sensor used, but some systems also incorporate gyroscopes or magnetometers. By analyzing gait, balance, and user position, wearable devices can accurately identify falls, making them a preferred solution due to their high accuracy and mobility (Özdemir, 2016).

Falls detection systems based on wearable devices use data from sensors that are worn by the users or integrated in the clothes. Most of the wearable sensors used are in the form of accelerometer devices (Igual et al., 2013). The accuracy of the systems depends on the sensors used and the type of classifications (Vallabh et al., 2016). This section explores current work on wearable devices - based falls detection systems.

4.2.1 Sensing Techniques for Fall Detection

Fall detection applications predominantly rely on wearable sensors, which can broadly be categorized into two types: those integrated within smartphones and those using external accelerometers.

Smartphone-Based Systems

Smartphones serve as a cost-effective and readily available platform for fall detection. They come equipped with an array of inexpensive MEMS sensors like accelerometers, gyroscopes, and magnetometers, providing a versatile foundation for computational analysis (Vallabh et al., 2016). For instance, the study by (Basili et al., 2016) used both a smartphone and an external accelerometer to assess a person's posture and identified potential falls based on threshold values of acceleration magnitudes.

Another notable approach (Kau & Chen, 2015) leverages a smartphone's tri-axial accelerometer and e-compass to determine the user's posture and motion. The system is particularly focused on older adults and features a warning sound and an emergency communication protocol using a 3G network. A variety of features are used to discern falls from other activities, and the system has demonstrated up to 92% sensitivity and 99.75% specificity in tests involving nine different types of activities.

However, there are limitations to smartphone-based systems. The performance is often tied to the quality of the embedded sensors, which varies between models and manufacturers (Casilari, Luque & Morón, 2015). Additionally, the sensitivity range of smartphone accelerometers is generally lower than that of specialized external sensors, posing limitations in certain scenarios.

Accelerometer-Based Systems

Accelerometers remain the most popular choice for fall detection outside the realm of smartphones (Nizam, Mohd & Jamil, 2016). These devices offer greater flexibility in terms of sensor placement on the body and often deliver higher sensitivity and specificity (Igual et al., 2013).

For example, a study by (Kangas et al., 2009) proposed three algorithms that use single-accelerometer data to detect various phases of a fall, such as the start, impact, and aftermath. These algorithms primarily focus on post-fall orientation to ascertain a fall event but do face limitations when rapid movements or tremors interfere with the sensor data (Pierleoni et al., 2015).

Another research effort (Özdemir, 2016) collected a comprehensive dataset from multiple body-worn sensors and applied machine learning techniques to evaluate the most effective sensor placements. The study found that waist-based sensors provide the highest sensitivity, especially when using k-NN classifiers.

In summary, while accelerometer-based systems generally offer higher performance, they do require more elaborate setup and calibration than their smartphone-based counterparts. Each approach comes with its own set of advantages and limitations, and the choice between them would depend on the specific requirements of a fall detection system.

4.2.2 Fall detection techniques

Falls detection systems operate based on the principle of distinguishing falls from other conventional movements which are called ADLs. Falls detection techniques can be classified into two categories: threshold-based approaches and pattern recognition methods (Habib et al., 2014). Threshold-based algorithms compare one or several magnitudes captured by the motion sensors with certain thresholds to make decision about activities detection. Pattern recognition methods base on diverse classification techniques such as SVM (Kau & Chen, 2015); (Özdemir, 2016); (Vallabh et al., 2016), k-NN (Özdemir, 2016); (Vallabh et al., 2016), ANNs (Özdemir, 2016); (Vallabh et al., 2016), Naive Bayes classifier (Vallabh et al., 2016), decision trees (Yuan, Tan, Lee & Koh, 2015), Hidden Markov Models (HMM), fuzzy logic. These methods comprise Artificial Intelligence, rule-based algorithms and machine learning-based algorithms (Casilari et al., 2015). Some of the threshold-based algorithms and machine learning-based algorithms that are applied widely in existing wearable devices-based falls detection systems are considered below.

Threshold-based algorithms

Threshold-based algorithms are applied in many existing falls detection application using wearable sensors such as smartphones (Basili et al., 2016); (Yildirim et al., 2016), or external accelerometers and other sensors (Kangas, Konttila, Winblad & Jamsa, 2007); (Kangas et al., 2009); (Ryu & Moon, 2016). In (Kangas et al., 2007), authors determined thresholds for total sum vector, dynamic sum vector, fast changes in acceleration signal, and vertical acceleration for falls detection algorithms using data gathered by a single accelerometer. A fall is detected by comparing one of the above four parameters with their defined thresholds and checking lying posture after falling. Results show that the algorithms can achieve high sensitivity and specificity up to 100%.

However, the algorithms use both threshold comparison and posture detection.

Threshold-based algorithms are simple to implement and have minimal computational work (Igual et al., 2013). Falls detection systems using smartphones are mainly limited by computing and storage capabilities. Hence, threshold-based algorithms are preferred in these systems. A simple application run in smartphones can implement threshold comparison straightforwardly and in real-time (Casilari et al., 2015). However, fall detection focusing only on large acceleration can result in many false positives. For example, the average value of SMV during running (2.3-2.8g) overlaps with this value during falling (2.4-5.4g) (Huynh, Nguyen, Irazabal, Ghassemian & Tran, 2015). To reduce false alarms, many works rely on detection of body orientation after falling. However these systems may be affected by activities with similar postures such as sleeping, reclining (Huynh et al., 2015).

Machine learning-based algorithms

In a study conducted by (Vallabh et al., 2016), five different classification algorithms including Naives Bayes, k-NN, LSM, ANN, and SVM were implemented and evaluated. Results show that with an accuracy of 87.5%, sensitivity of 90.70% and specificity of 83.78%, k-NN is the best classifier. Compare to LSM and Naive Bayes, the k-NN, ANN, and SVM had the better accuracy and are viable options for implementation.

In (Yuan et al., 2015), ADL classification algorithm is developed based on decision tree learning. Three picking up and putting down objects are identified as false positives. The proposed algorithms are more power-efficient than conventional algorithms due to allowing to process accelerometer data completely locally. However, these algorithms need to be developed for eliminating false negatives.

Compare to threshold-based algorithms, machine learning based algorithms are more sophisticated, however if they lead to better detection is questionable. Nevertheless, the machine learning algorithms demand high mathematical skills and are computationally intensive (Igual et al., 2013) that may not respond in real-time (Huynh et al., 2015). Results from (Aziz, Musngi, Park, Mori & Robinovitch, 2017) show that all the five machine learning algorithms in their research (Logistic Regression, Naive Bayes, k-NN, Decision tree, and SVM) provided sensitivity and specificity of at least 90%, while the studied threshold-based algorithms (Kangas2Phase, Kangas3Phase, BourkeUFT, BourkeLFT, and Bourke4Phase) have sensitivity and specificity from 0 to 100%.

The effectiveness of machine learning algorithms versus threshold based is not the focus of this paper, but based on the literature review above we decided to apply threshold based approach as it offers more accuracy and simplicity. We also found the algorithms in the studies reviewed are not clearly documented, therefore we not only present the experimentation data, but a clear articulation of the algorithm is accompanied in the following sections.

4.3 Proposed Fall Detection Algorithm

The scope of this section is to determine the parameters and thresholds for falls detection, using motion data measured by an accelerometer.

4.3.1 Data collection

In many falls detection algorithms based on threshold approach, falls are identified by comparing SMV with upper and/or lower thresholds (Basili et al., 2016); (Huynh et al., 2015); (Kangas et al., 2007); (Sprute, Pörtner, Weinitschke & König, 2015), and the thresholds are determined by experimentation in many studies (Huynh et al., 2015). Similarly, this study gathered motion data using a single tri-axial accelerometer and analyzed the collected data to investigate the difference between accelerations in falling and ADL. The results were used to develop our algorithm.

The device used to collect motion data in this work is the accelerometer model X8M-3 (Concepts, 2012). With the attached position of the accelerometer, the measured data *Ax, Ay, Az* correspond to accelerations in the three following axes: X (lateral: left - right), Y (vertical: up - down), and Z (direction: front - back).

Intentional falls including forward, backward, left-side and right-side falls and ADLs including walking, sitting, standing and lying were performed by one subject (female, aged 36 years). Accelerations during these activities were measured with the accelerometer attached on the chest of the person which is the same place as in (Huynh et al., 2015); (Kau & Chen, 2015). The position of the accelerometer was identical all the times when data were collected.

Sample patterns (Table 4.1) was collected to identify the difference in acceleration between falling and ADL. Test patterns (Table 4.2) was collected including 32 datasets, each dataset consists of a mixed set of activities (walking, sitting, standing, falling, lying, standing up). These patterns are used for validation to determine the sensitivity, specificity, and accuracy of ACFDA.

Table 4.1: Number of activities in sample patterns

Activities	Number
Walking	20
Standing	20
Sitting	20
Lying	20
Falling	20

Table 4.2: Number of activities in test patterns

Activities	Falling	Idle	Standing up	Walking
Number	44	126	56	48

4.3.2 Data Analysis

Data analysis was performed using MATLAB program to find the maximum, minimum, and average values of accelerations in each axes and in the SMV for each of the following activities: falling, walking, standing, sitting, and lying.

Algorithm 1 summarizes the data analysis process. Raw acceleration data collected in sample patterns are loaded from accelerometer to a computer (line 1) and are converted to gravity unit (line 2). SMV is calculated for each sample point (line 3). The maximum, minimum, and average values of accelerations in each axis (x, y, z) and in the SMV are identified (line 4).

Algorithm 1 Pseudocode code for Data Analysis

Input: Raw data (t, Ax, Ay, Az) from Accelerometer.
Output: max, min, average of x, y, z, SMV.
Method:

1: Receive raw data (t, Ax, Ay, Az) from Accelerometer.
2: Convert raw accelerations (Ax, Ay, Az) into normalized accelerations (x, y, z).
3: Calculate SMV.
4: Find max, min, average of x, y, z, SMV.
5: When End of data ⇒ **Exit**.

Data analysis results shows that SMV of acceleration in standing, sitting and lying patterns are nearly the same at around 1g. These activities are grouped into one state called *Idle*.

The rapid change of acceleration in vertical axis (*y_diff*) in falling, walking, and *Idle* states was calculated using the difference between the maximum and minimum values in the period of time that activities occurred. These changes of falls and ADLs are shown in Figure 4.2. As being illustrated in this Figure, acceleration in vertical axis in falling activity has the most fluctuation which is usually larger than 2g. While this value in walking activity and *Idle* state are around 1g and 0g, respectively. There is no overlapping in this Figure 4.2, which helps us propose a fall detection algorithm based on acceleration change.

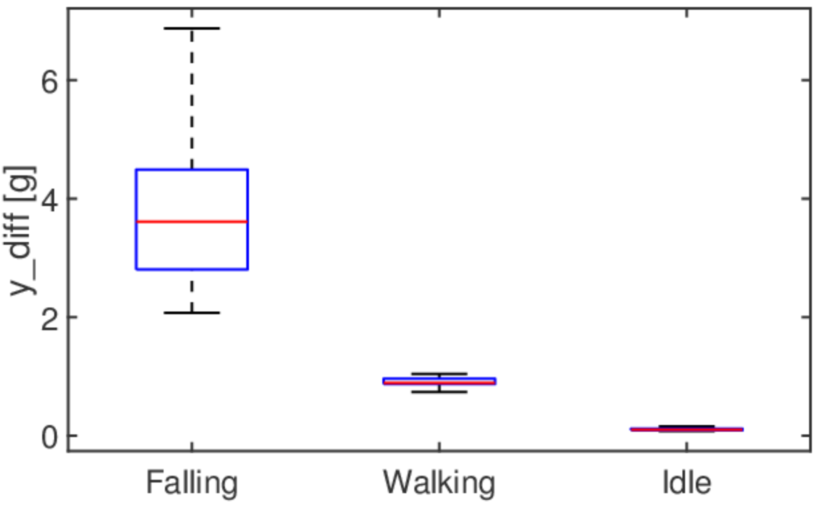


Figure 4.2: Difference between maximum and minimum values of acceleration in vertical

4.3.3 Acceleration Change-based Falls Detection Algorithm (ACFDA)

Algorithm 2 Pseudocode code for ACFDA

Input: Raw data (t, Ax, Ay, Az) from Accelerometer.
Output: Falls detection results.
Parameters: window length (w); detection interval (d); threshold for y_diff (th_y); threshold for $SMV\_average$ (th_S).
Method:

1: Initialize parameters:
w = 2s; d = 1; $th_y = th$; th_S = 1.1g.
2: Receive raw data (t, Ax, Ay, Az) from Accelerometer.
3: Convert raw accelerations (Ax, Ay, Az) into normalized accelerations (x, y, z).
4: Analyze the normalized data in each 2s window to find:
y_max; y_min; $y\_average$; y_diff; SMV; $SMV\_average$.
5: If (y_diff >= th_y) and ($SMV\_average$ >= th_S) then **Falling**.
6: Else **Normal activities**.
7: When End of data ⇒ **Exit**.

We proposed our algorithm (Algorithm 2) based on defining thresholds for *the rapid change of acceleration in vertical axis* (*y_diff*) and *the average value of SMV* (*SMV_average*) which is summarized in the pseudo-code below. This algorithm allows to identify falls from normal daily activities including walking, standing, sitting, lying and standing up after falling. The algorithm was computed in MATLAB program.

4.4 Evaluation the Proposed Fall Detection Algorithm

4.4.1 Performance Evaluation

In general most falls detecting algorithms can produce the following four possible outcomes:

- True Positive (TP): a fall is detected properly.

- False Positive (FP): a fall is detected when no fall has occurred. This outcome also is known as false alarm.

- True Negative (TN): no fall is detected when no fall has occurred.

- False Negative (FN): no fall is detected when a fall has occurred. This case is also called missed fall.

Based on these possible outcomes, the performance of the algorithm is represented including sensitivity, specificity, and accuracy which are given by (Aguiar, Rocha, Silva & Sousa, 2014):

$$Sensitivity = \frac{TP}{TP + FN} * 100 \tag{4.1}$$

$$Specificity = \frac{TN}{FP + TN} * 100 \tag{4.2}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} * 100 \tag{4.3}$$

Sensitivity is the ratio between truly identified falls and all falls which defines how successfully the algorithm detects falls. Specificity is the proportion of the algorithm to correctly identify ADLs and indicates how successfully the algorithm detects ADLs.

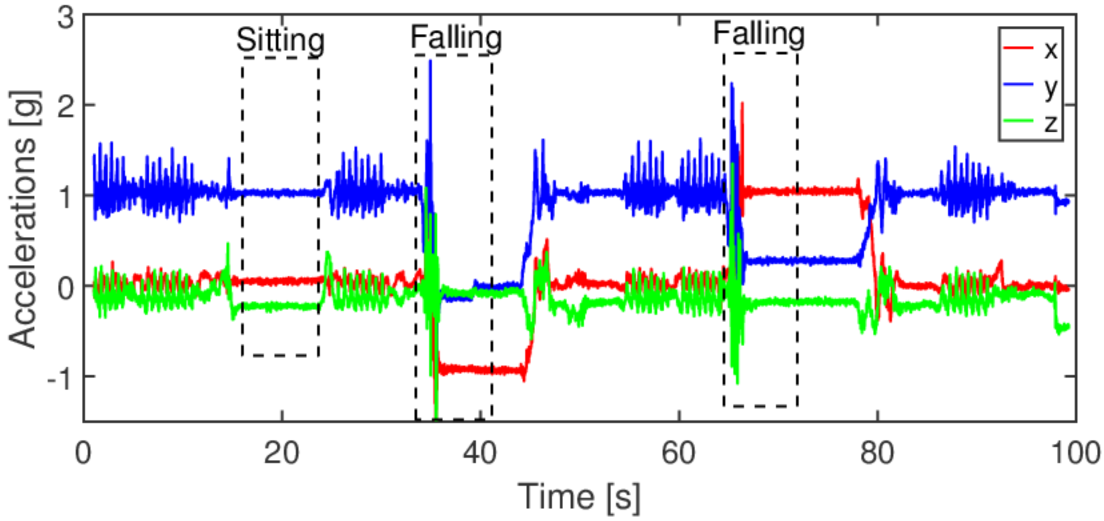


Figure 4.3: An example of testing pattern

Accuracy indicates how well the algorithms identify both falls and ADLs. It is derived from the rate between truly give decisions and all decisions.

4.4.2 Testing ACFDA on accelerometer data

To test our algorithm, test patterns were applied as inputs for falls detecting program. A total of 32 test patterns were tested. The number of each activities in the test patterns was summarized in Table 4.2.

An example of testing pattern is illustrated in Figure 4.3. In this pattern, data were collected when user performed the following activities: walking (10s), standing (5s), sitting (10s), walking (10s), left-side falling and lying (10s), standing up and standing (10s), walking (10s), right-side falling and lying (10s), standing up and standing (10s), walking (10s), and standing (5s). Data are represented in this Figure are normalized accelerations in three axes. The result of applying our proposed algorithm with th_y = 2.0g and th_S = 1.1g on this testing pattern is illustrated in Figure 4.4. In this pattern, two falls are detected correctly, and all other activities are identified as ADLs.

Table 4.3 shows the performance of the ACFDA with different chosen thresholds

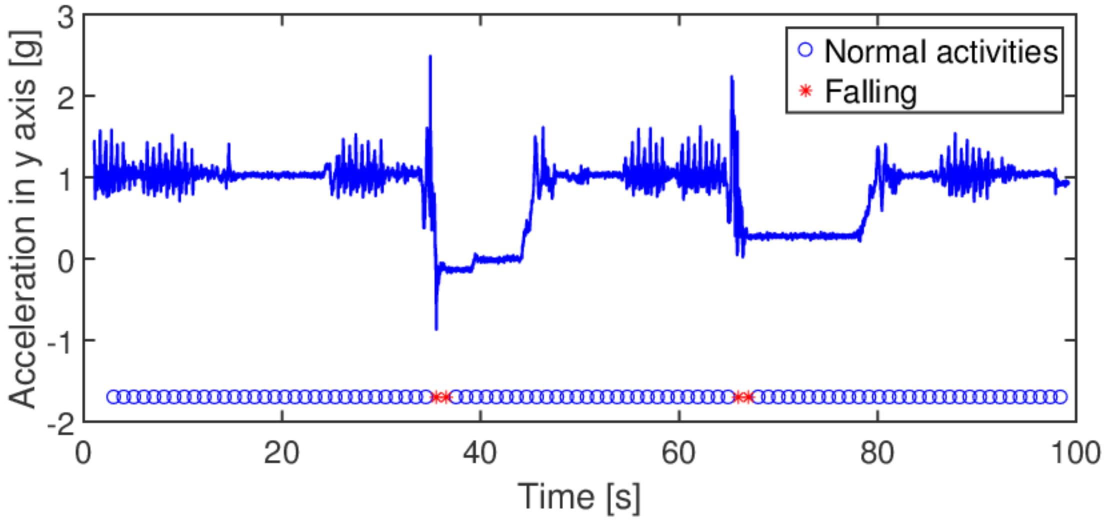


Figure 4.4: Falls detection result

for the fast change in y-acceleration.

Table 4.3: Performance of the ACFDA

th [g]	TP	TN	FP	FN	Sensitivity	Specificity	Accuracy
2.0	41	226	4	3	93.18%	98.26%	97.45%
1.6	43	225	5	1	97.73%	97.83%	97.81%
1.3	44	220	10	0	100%	95.65%	96.35%

When the threshold (th_y) is set to 2g, ACFDA can detect 41 out of 44 falls, it cannot detect 3 falls, 4 standing up states after falling are detected as falls. In this case, the algorithm achieves 93,18% of sensitivity, 98.26% of specificity and 97.45% of accuracy. However, false negative need to be eliminated because it may be dangerous for users if a fall occurs but the system cannot detect it. A simplest way to improve sensitivity of the algorithm is to decrease th_y.

When th_y is decreased, the number of falls which are detected increases. It results in the increase in sensitivity. This is because when a high threshold is set, some weaker falls may be classified as safe activities. However, when a low threshold is set, fall positives may increase because strong daily activities may be classified as falls. As we can see from Table 4.3, when th_y is selected as 1.6g, the number of false negative decreases from 3 to 1 comparing to th_y = 2.0g, while the number of false positive increases from 4 to 5. The sensitivity and accuracy of the algorithm are improved, although the specificity reduces slightly. When th_y is chosen as 1.3g, all falls in the test patterns are detected correctly, however the number of false positive increase to 10, resulting to the reduction in both specificity and accuracy of the algorithm. In this experimentation, all the false positive cases are the result of the *standing up* states after falling.

An algorithm having high scores for all sensitivity, specificity and accuracy is desirable. However, in term of the key purpose of falls detection, it can be pointed out that the success of the algorithm mostly depends on the frequency of false negative because it is the most dangerous and unwanted case (Özdemir, 2016). False negative is a serious mistake for the algorithm and for a reliability of the system, hence it is expected to be 0. Falls detection systems must achieve very high score in sensitivity and accept the trade-off between sensitivity and specificity. False positive is a lesser concern, however it needs to be avoided as well to prevent confusion and unnecessary escalation (Özdemir, 2016).Compared to previous works ((Yildirim et al., 2016), (Yuan et al., 2015)) , our ACFDA has all the three performance ratio including sensitivity, specificity and accuracy above 90% for three chosen thresholds for *y_diff*.

4.4.3 Testing ACFDA on smartphone built-in accelerometer data

Motion data was collected using two smartphones Nexus 4 (Nexus, 2012) and Nubia NX511j (Nubia, 2015). Acceleration data was collected by the application named Physics Toolbox Accelerometer (Google, 2017) installed on the smartphones.

The number of each activities in sample data and test data is summarized in Table 4.4.

Table 4.4: Number of activities in sample data and test data

Activities	Sample data	Test data	Total Number
Walking	10	62	72
Bending	10	63	73
Lying	10	71	81
Sitting	10	64	74
Standing	10	*	10
Backward falling	10	10	20
Forward falling	10	10	20
Left side falling	10	10	20
Right side falling	10	10	20

** Standing activity was not counted in test data since it is the idle activity performed between other activities.*

Figures 4.5 and 4.6 illustrate sample and test data segments. The former contains a falling event, while the latter comprises a variety of activities including walking, lying, falling, and sitting.

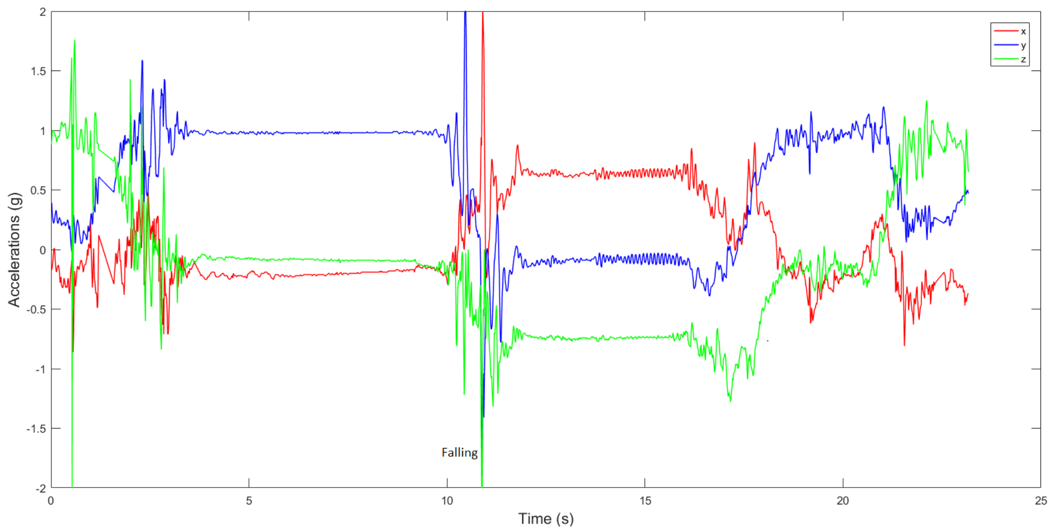


Figure 4.5: Example of sample data showing a fall

Table 4.5 presents the performance of ACFDA under varying thresholds using data collected by smartphone 1 (Nexus 4). These thresholds were derived from our initial data analysis, which indicated that the majority of falls result in *y_diff* values exceeding 2.0g. As a result, three separate th_y values were used for evaluation. Simultaneously,

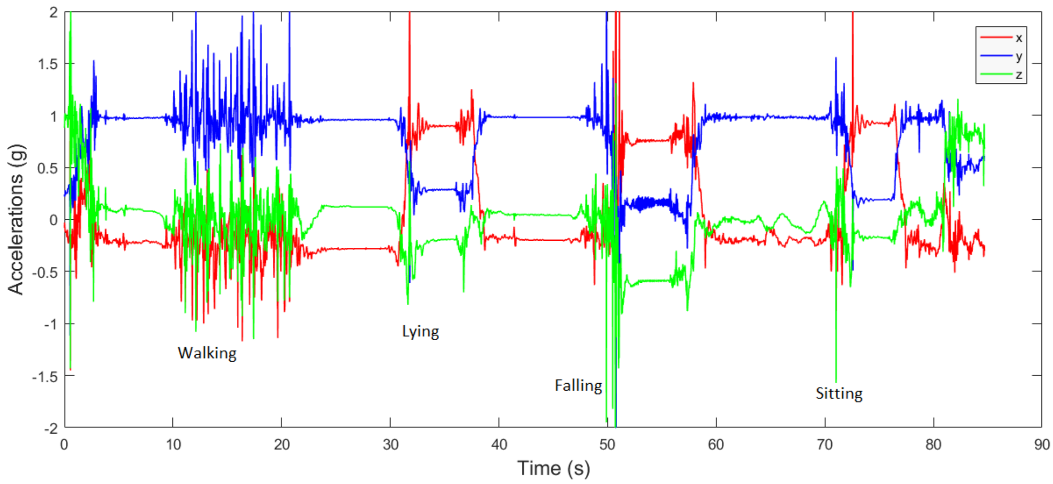


Figure 4.6: Example of test data

the average *SMV* value for all falls approximated 1.0g, warranting its selection as the th_S value.

Table 4.6 shows the evaluation result of performance of the ACFDA with different thresholds of *y_diff* and *SMV_average* using data collected by smartphone 2 (Nubia NX511j). The thresholds for *y_diff* and *SMV_average* were chosen as in the experiment with smartphone 1.

Table 4.7 summaries the evaluation result of performance of the ACFDA with different thresholds of *y_diff* and *SMV_average* when tested on data collected by accelerometer (Concepts, 2012), smartphone 1 (Nexus 4) and smartphone 2 (Nubia NX511j). The first and second columns are chosen thresholds for *y_diff* and *SMV_average*. The third column shows sensitivity (Se) and specificity (Sp) when ACFDA is tested with data collected by accelerometer (acc). The forth column shows Se and Sp when ACFDA is tested with data collected by smartphone 1- Nexus 4 (sp1). And the fifth column shows Se and Sp when ACFDA is tested with data collected by smartphone 2 - Nubia NX511j (sp2).

This research focused on differentiate falls from slow motion activities. However, daily living activities consist of various activities which have slow or fast changes in

Table 4.5: Performance of the ACFDA test on smartphone 1 (Nexus 4)

th_y	th_S	True Positive	False Positive	True Negative	False Negative
2.0	1.0	40	4	256	0
2.0	1.1	27	0	260	13
2.4	1.0	38	3	257	2
2.4	1.1	27	0	260	13
2.6	1.0	38	1	259	2
2.6	1.1	27	0	260	13

th_y,th_S: [g]

Table 4.6: Performance of the ACFDA test on smartphone 2 (Nubia NX511j)

th_y	th_S	True Positive	False Positive	True Negative	False Negative
2.0	1.0	19	0	15	1
2.0	1.1	11	0	15	9
2.4	1.0	18	0	15	2
2.4	1.1	9	0	15	11
2.6	1.0	16	0	15	4
2.6	1.1	8	0	15	12

th_y,th_S: [g]

accelerations. Falls may not be differentiated from fast motion activities such as running or jumping based on determining lower thresholds for fast change of acceleration in vertical axis and the average value of SMV. In order to identify falls from these strong activities, ACFDA need to be improved. Furthermore, the changes of accelerations in X, Y, and Z axes could be analyzed to identify the orientation of falling activity including frontward fall, backward fall, left-side fall, and right-side fall. This analysis may be useful for distinguishing lying between other idle states as well.

4.5 Chapter Summary

This chapter has presented an in-depth analysis of wearable sensor-based fall detection, underlining the critical role of machine learning techniques, acceleration signal analysis, and threshold-based detection. The findings from numerous studies and our own experiments revealed that these mechanisms play a significant role in distinguishing

Table 4.7: Performance of the ACFDA

th_y	th_S	X8M-3			Nexus 4			Nubia NX511j		
		Se	Sp	Acc	Se	Sp	Acc	Se	Sp	Acc
2.0	1.0	93.18	97.39	95.99	100	98.46	98.66	95	100	97.14
2.0	1.1	93.18	98.26	97.45	67.5	100	95.67	55	100	74.29
2.4	1.0	75	98.7	94.89	95	98.85	98.33	90	100	94.29
2.4	1.1	75	99.57	95.62	67.5	100	95.67	45	100	68.57
2.6	1.0	72.72	100	95.62	95	99.6	99	80	100	88.57
2.6	1.1	72.72	100	95.62	67.5	100	95.67	40	100	65.71

th_y,th_S: [g]
Se, Sp, Acc: [%]

between Activities of Daily Living (ADLs) and fall events, even though the task is inherently challenging due to the overlap in acceleration patterns.

Our algorithm, Acceleration Change-based Fall Detection Algorithm (ACFDA), uses thresholds for rapid changes in acceleration in the vertical axis and the average value of the Scalar Magnitude Vector (SMV). It showed promising results in preliminary tests, especially when the optimal thresholds are carefully selected to minimize false negatives.

However, the problem of false positives remains an area for future work, especially in scenarios where high-intensity activities like running or jumping might be misclassified as falls. The results also emphasized the need to consider device-specific thresholds to achieve the highest sensitivity and specificity, thus highlighting the intricate interplay between hardware and algorithm design in fall detection.

Lastly, this study highlighted the possibility of identifying the orientation of falling activity, which could be a valuable contribution to the development of more sophisticated fall detection and response systems. Future research may expand on this concept and investigate more nuanced aspects of fall detection, such as differentiating between various types of falls and using additional sensor data for even more accurate classification.

In conclusion, the complexity of fall detection algorithms reflects the complexity of human movement itself. Despite this challenge, progress in sensor technology and machine learning promises to continue improving the safety and quality of life for at-risk individuals.

Chapter 5

Visual Object-based Fall Detection

5.1 Introduction

As seen in the previous Chapter 4, wearable sensors can be used to detect some activities of people who are wearing them. Fall detection could be achievable. In fact, there are many research articles related to that. For instance, SmartFall (Mauldin, Canby, Metsis, Ngu & Rivera, 2018) is a framework fall detection framework using smartwatches for fall detection system using deep learning. Or a combination of smartphone and smart watch can be used to detect falls, in (Vilarinho et al., 2015).

However, wearable devices are noticeably uncomfortable to have them one all the time. A survey on "Consumers' perceived attitudes to wearable devices in health monitoring in China" (Wen, Zhang & Lei, 2017) has indicated that half of the people who asked, defined the main issues for not using wearable devices:

- Short battery time
- Ease of being damaged
- Uncomfortable to wear
- Technical immaturity

- Inaccurate data recording

- Unattractive features

Environmental sensor based or context-aware fall detection systems can eliminate the above issues. These systems detect falls by utilizing visual sensors, laser diodes, radars, infrared sensors and pressure sensors that are attached on the environment. The main advantages of context-aware systems over wearable sensors systems are eliminating the need for wearing sensors all the time and avoiding the anxiety for forgetting to carry sensors. However, there are limitations such as spatial coverage of installed environment sensors and user privacy which makes them feel being watched all the time.

5.2 Related Work

Depth sensor such as Microsoft Kinect is used in some systems for differentiating human falls from other activities based calculating motion related features such as velocity, acceleration and position (Jagtap, Angal, Student & BSIOTR, 2016; Nizam, Mohd, Tomari & Jamil, 2016). If unusual activity is detected, systems send alerts to users' caregivers using GSM. A robot with camera vision at home is designed by (Juang & Wu, 2015) for identifying fall-down movements of elderly people in real-time using triangle pattern rule. The system achieves 90% of accuracy under a single character posture and up to 100% under a continuous-time sampling criterion with using Support Vector Machine (SVM) classifier.

In a research conducted by (De Backere et al., 2015), authors presented a system called FallRisk which is a social and context-aware multi-sensor falls detection and risk assessment platform consists of sensors, a local gateway, a controller and OCarePlatform in the Cloud. Contextual information and fall estimation and detection is sent back to the Controller for notifying the caregivers or the emergency response center. Majumder et al. (Majumder et al., 2016) designed and implemented a smart-shoe which can warn the user about their abnormal gait and possibly save them from a forthcoming injuries. The system uses the piezoresistive sensor attached in the shoe to collect the raw insole pressure data while the user is walking. This data is then compared with the gait event parameter of the biomechanical model. The resulting outputs are processed inside the mobile phone to identify the user's gait pattern. If the gait pattern reaches a certain threshold where the user might face a potential fall, the system triggers a warning to the user with a message and vibration.

5.3 Visual Object-based Fall Detection Algorithm

5.3.1 Proposed Fall Detection Algorithm

The proposed fall detection algorithm serves as an integrated system incorporating four principal components: Video Capture and Playback, Pose Landmark Detection, Fall Recognition, and User Interface Interactivity. These integral modules collaborate to process video streams, capture human pose landmarks, recognize fall incidents, and finally, update the user interface in real-time. Below are the brief explanations for each component:

- **Video Capture and Playback**: This is the initial stage where the algorithm captures video data, either in real-time or from a pre-recorded source. The video is processed frame by frame, and certain frames are selectively blurred to focus on the subject.

- **Pose Landmark Detection**: In this stage, the MediaPipe library is utilized to detect and plot human pose landmarks on the processed video frames. These landmarks are key points on the human body, like the nose, hips, and other joints, which are essential for detecting a fall.

- **Fall Recognition**: This component leverages the pose landmarks to detect a fall incident. Specifically, it monitors the vertical distance between the nose and hip landmarks. If this distance falls below a specified threshold, the system recognizes it as a fall event, updates the skeleton color, and overlays a 'FALL DETECTED' text on the frame.

- **User Interface Interactivity**: The algorithm is encapsulated in a user-friendly GUI developed using Tkinter. This interface features a video display panel and a dropdown menu for video file selection, thereby offering a seamless user experience.

By synergizing these components, the system effectively performs real-time fall detection and can promptly alert caregivers or medical professionals, proving its potential utility in healthcare and surveillance applications.

Pose Landmark Detection and Processing

The initial and crucial step in our algorithm revolves around detecting human pose landmarks in the video frames being analyzed. This is achieved using the MediaPipe Pose model, a solution specifically designed for real-time pose estimation. An illustrative example of pose detection carried out using this model is depicted in Figure 5.1.

Going into more detail, MediaPipe Pose operates in real-time and is capable of detecting 33 pose landmarks on the human body, such as the nose, hips, and other joints. These landmarks are essential for the subsequent stages of the algorithm, especially fall detection. Due to its efficient architecture, MediaPipe Pose offers a compelling balance between computational load and accuracy, making it suitable for real-time applications.

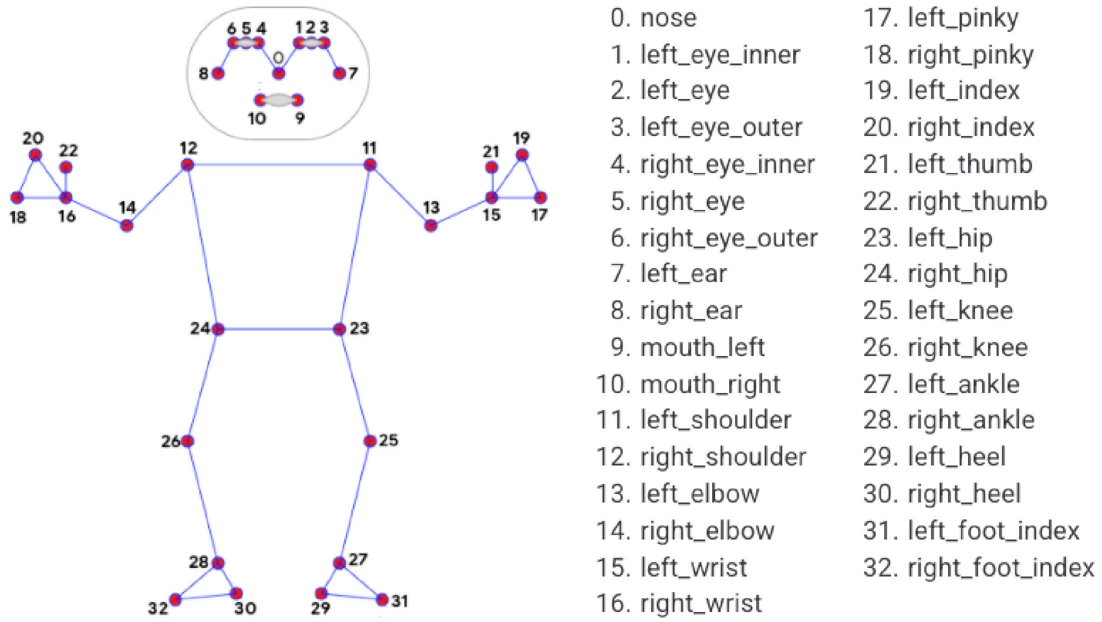


Figure 5.1: Pose detection leveraging the MediaPipe Pose model (Kim, Choi, Ha & Choi, 2023)

Transitioning from pose landmark detection to fall detection, the algorithm calculates the distance between specific landmarks—specifically, the nose and the hips. By monitoring this distance and applying a threshold value, the algorithm is capable of reliably identifying fall incidents. The algorithm employs conditional logic to change visual cues on the video frame, such as the color of the skeleton and overlay text, when a fall is detected.

Fall Detection and Post-Processing

The third stage in our algorithm focuses on the recognition of fall actions, which is directly accomplished using the previously detected pose landmarks. In contrast to using more complex models like Spatial-Temporal Graph Convolutional Networks (STGCN), our approach leverages a more straightforward method to detect falls in real-time.

By monitoring the Y-axis positions of specific pose landmarks such as the nose and both hips, the algorithm assesses the vertical distance between these points. If the distance falls below a certain threshold, it triggers the fall detection mechanism. Specifically, the algorithm checks if the absolute difference between the Y-axis coordinate of the nose and those of the left and right hips are below 0.125. If either condition is met, a fall is considered to have occurred.

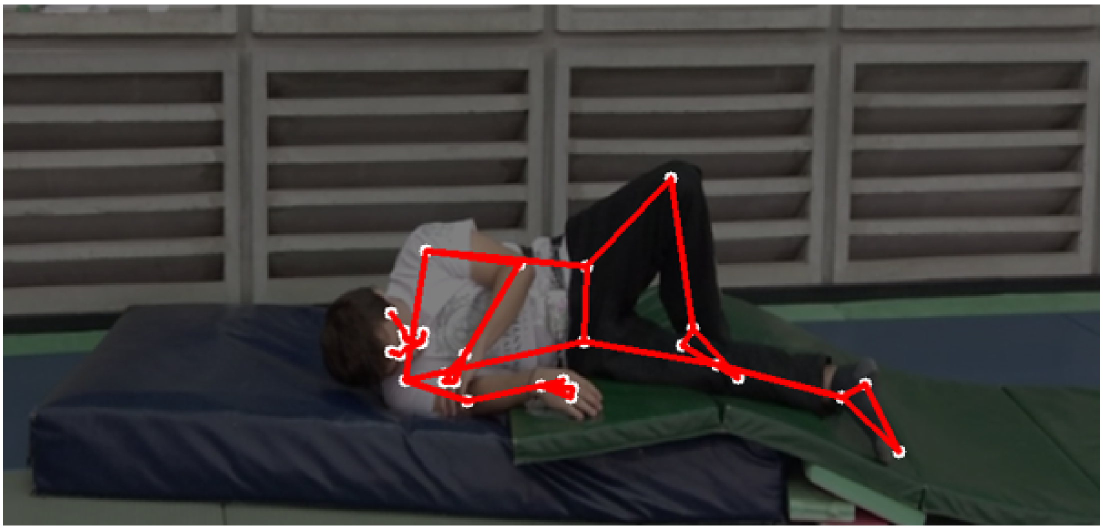


Figure 5.2: Illustration of a detected fall within real-time video footage using the proposed algorithm.

For the final step, post-processing is employed to reduce the chances of false positives. The algorithm dynamically alters the sampling rate of the video frames to more closely scrutinize potential fall incidents. This is achieved by incrementing a ‘step‘ variable which adjusts the rate at which video frames are analyzed. When a fall is detected, the skeleton in the video is colored red and a ’FALL DETECTED’ label appears on the screen, providing immediate visual feedback.

In summary, our fall detection algorithm, with its streamlined methodology, promises real-time processing combined with high accuracy, thereby enabling quick alerts and timely interventions.

5.3.2 Dataset

In the pursuit of validating the efficacy of our fall detection algorithm, we leveraged the SysFall dataset, an extensive and publicly available collection of data pertaining to fall and movement detection. Created by Angela Sucerquia, José David López, and Jesús Francisco Vargas-Bonilla, this dataset provides a well-documented collection of both Activities of Daily Living (ADLs) and fall events. Recorded with a self-developed device featuring dual accelerometers and a gyroscope, the SysFall dataset comprises a wide range of movements performed by two distinct age groups—23 young adults aged between 19 to 30, and 15 elderly participants aged between 60 to 75. It uniquely includes 19 types of ADLs and 15 types of falls, making it an invaluable resource for benchmarking fall detection algorithms.

5.3.3 Data Analysis

Our primary focus during the data analysis was to extract relevant features and patterns that could efficiently distinguish between a fall and other everyday activities. We particularly analyzed the 15 different types of falls categorized in the SysFall dataset, which range from ’Fall forward while walking caused by a slip’ to ’Lateral fall while sitting, caused by fainting or falling asleep.’ The dataset’s richness in capturing both acceleration and rotation across multiple trials provided a nuanced view of the characteristics that typify a fall.

5.3.4 Evaluation

To assess the robustness and accuracy of our algorithm, we conducted extensive tests using the 15 fall types specified in the SysFall dataset. Remarkably, our algorithm successfully identified falls in every single one of the 15 test videos from the dataset, substantiating its reliability and efficiency. This comprehensive evaluation underscores the capability of our fall detection model to not only learn from but also correctly classify complex human activities. With a flawless detection rate on the SysFall dataset, we are confident that our algorithm holds significant promise for real-world applications, particularly for the vulnerable elderly population, thereby enabling prompt medical intervention.

5.3.5 Fall Detection GUI Implementation

To offer a more intuitive understanding, we developed a Graphical User Interface (GUI) that encapsulates the entire fall detection process. Our system leans on a variety of Python libraries, namely OpenCV (cv2), MediaPipe (mp), Tkinter (tk), NumPy (np), and PIL (Image, ImageTk). Pose landmarks are at the heart of our fall detection logic. The GUI can be downloaded at `https://psivt2023.aut.ac.nz/fallGUI.zip`.

Initialization of Libraries and Global Variables

At the outset, we initialize MediaPipe's drawing and pose solutions, along with setting up the global variables. These variables, such as 'after_id' and 'cap', serve the purpose of managing video playback. Furthermore, we instantiate a pose object from MediaPipe and initialize a 'step' variable to control frame rates during video streaming.

Halting Video Playback

The 'stop_video' function is designed to cease video streaming effectively. It cancels any queued Tkinter 'after' events and releases the VideoCapture object from OpenCV.

Fall Detection Mechanism

The core function, 'detect_fall', computes the occurrence of a fall based on specified pose landmarks: the nose, left hip, and right hip. If the vertical distance between the nose and either hip falls below a preset threshold (0.125), the system recognizes it as a fall event.

Visualizing Pose Landmarks

For better visualization, our ‘draw_connections‘ function overlays a skeleton onto the video frames, connected via pose landmarks. The color schema for these connecting lines can be customized through a color tuple parameter.

Video Processing and Playback

The function ‘play_video‘ is the cornerstone of the application, encompassing the following functionalities:

- Frame-by-frame video reading
- Application of Gaussian blur on video background
- Pose landmarks detection and rendering
- Fall detection, with visual alterations on the skeleton and a text overlay indicating ‘FALL DETECTED‘.

Moreover, the function updates the GUI with each new frame while maintaining a regulated frame count to optimize processing.

Video File Selection

The GUI features a dropdown menu that allows users to select a video for analysis from the ’dataset’ directory. Upon selecting a video, the function ‘on_select‘ initializes the video stream and triggers the ‘play_video‘ function to start playback.

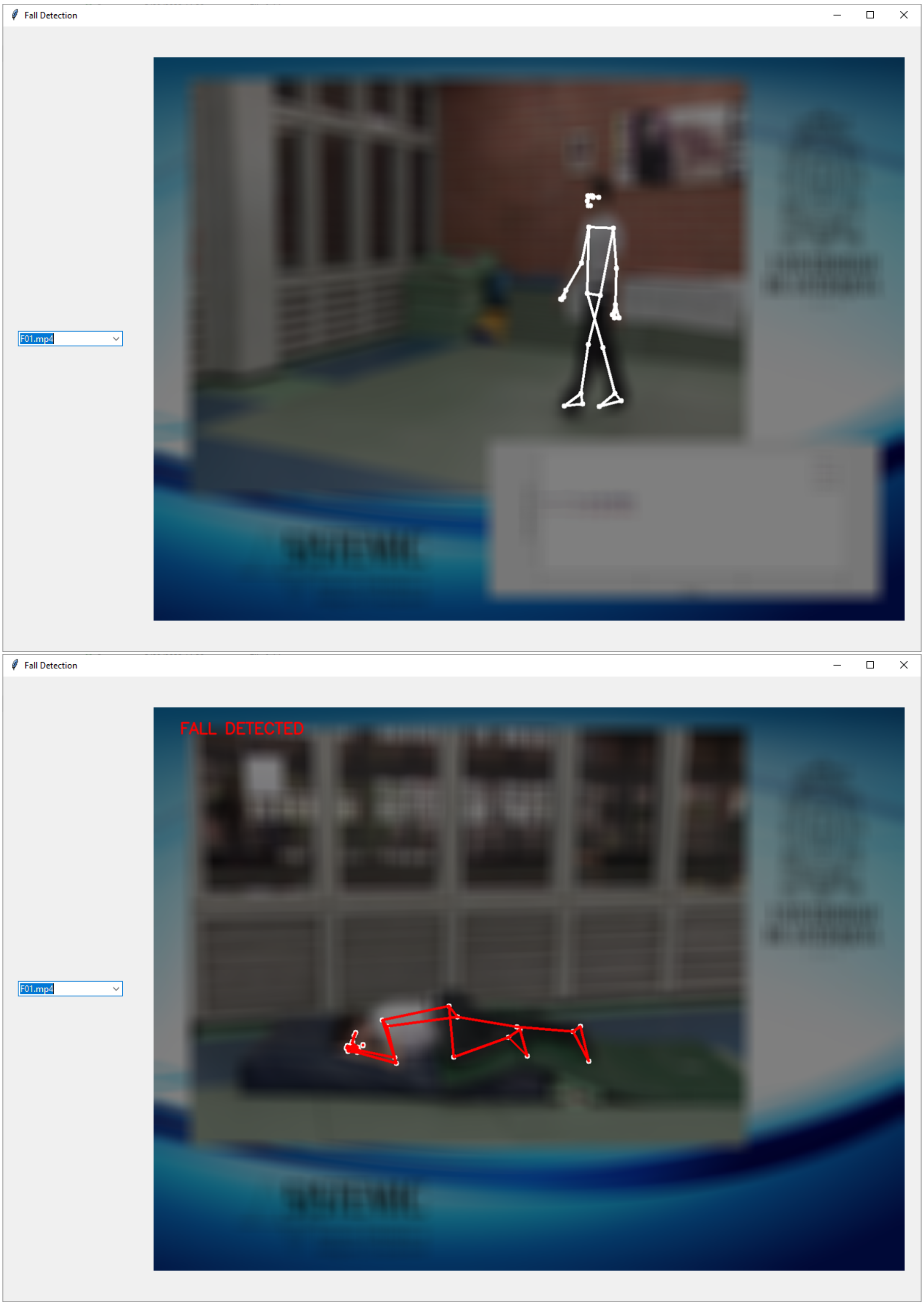


Figure 5.3: Fall Detection Application

Layout and Design of GUI

The GUI, designed using Tkinter, splits into two frames: the left frame hosts the dropdown menu for video selection, and the right one displays the video feed (See Figure 5.3). The Tkinter ‘mainloop‘ function sustains the application.

5.4 Chapter Summary

Our system adroitly integrates elements of computer vision, machine learning, and GUI design to form a comprehensive solution for fall detection. By efficiently analyzing real-time pose landmarks, it demonstrates significant potential for healthcare applications, especially in identifying fall events.

Chapter 6

Preserving Privacy through Visual Content Hiding

6.1 Introduction

The growing reliance on automated fall detection systems brings forth questions about their accuracy and reliability. Although these systems have advanced significantly, their predictions are not always infallible. Incorrect detections can have serious ramifications, necessitating verification from a third-party individual such as a caregiver or medical professional. However, transmitting visual footage of the individual experiencing the fall over the internet poses serious privacy concerns. This chapter proposes two privacy-preserving methods for manual verification of fall incidents: skeletal pose imaging (covered in Section 6.2) and visual encryption (covered in Section 6.3).

6.2 Skeletal Pose Imaging

This section introduces a privacy-preserving methodology for fall detection that transmits only the skeletal or pose data of the individual. The skeleton data sufficiently captures fall events while preserving an individual's privacy by not showing their full visual appearance.

6.2.1 Human Skeleton Extraction

To extract the human skeleton data, we utilize the MediaPipe framework. MediaPipe offers impressive performance in human pose estimation by providing a set of key points that represent various joints on the human body. These points encode vital information about joint movements and trajectories, which are essential for our algorithm focused on fall detection.

Key Joint Points and Their Significance

The key points identified by the MediaPipe framework are crucial for action recognition, particularly for detecting falls. This subsection explores the anatomy of these points and their importance in our algorithm.

Exclusion of Facial Points

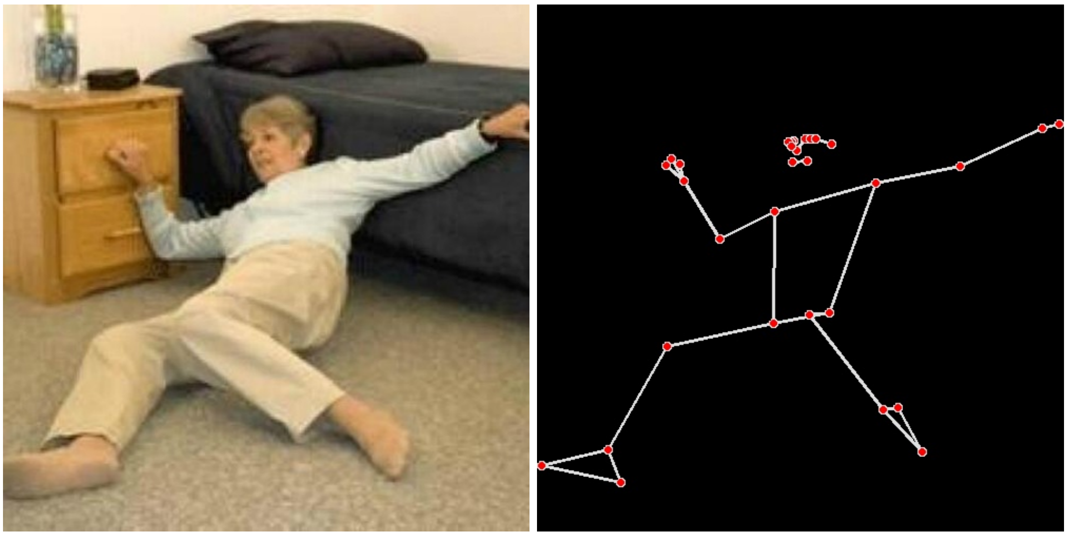
Facially descriptive points are intentionally excluded to maintain a focus on fall detection and to preserve privacy. This subsection elaborates on the rationale behind this decision.

6.2.2 Rationale for Employing Skeleton-Only Transmission

Transmitting only skeletal or pose data provides multiple advantages, including:

1. **Identity Protection:** This method abstracts away from identifiable facial and bodily features, ensuring anonymity.

2. **Data Minimization:** Only essential skeletal data is transmitted, reducing data volume and enabling faster real-time processing.



(a) Detected Fall Event (b) Skeleton During Fall

Figure 6.1: Skeleton detected using MediaPipe framework.

3. **Regulatory Compliance:** This approach is in line with global privacy regulations, such as the GDPR in Europe.

4. **Public Acceptance:** The privacy-preserving nature of this method is likely to receive better public and stakeholder acceptance.

5. **Flexibility and Scalability:** The extracted skeletal data can be easily integrated into various systems and scales well.

6. **Focused Analytics:** The algorithm focuses only on essential skeletal data, enabling more accurate and efficient fall detection.

6.2.3 Securing Trust and Ensuring Robustness

The choice to transmit only skeletal data isn't solely a technical decision but also embodies a commitment to user privacy. In the context of growing concerns about digital surveillance and data breaches, our approach aims to strike a balance between efficacy in fall detection and respect for individual privacy. We aim to build user trust by demonstrating that advancements in this field can be both effective and ethical.

6.3 Visual Encryption

The second method aims to address privacy concerns by encrypting the visual footage before transmission. Only authorized parties possessing a unique private key can decrypt the footage to verify the fall. This ensures that the individual's privacy is maintained while still allowing for manual verification of the detected fall.

Here, we introduce a rapid and secure method for concealing visual content, as illustrated in Fig. 6.3. Our system effectively preserves visual content even after lossy compression, manipulation, and transmission of images and video streams over the Internet. The resulting images and videos appear as random patterns, making them unrecognizable to general viewers. This approach allows for the transfer of visual content through public domains such as Dropbox, Pixabay, YouTube, Dailymotion, Vimeo, or other public sharing servers.

While most providers offer free storage space, their focus tends to be on managing large amounts of data rather than maintaining high quality. For example, YouTube processes over 300 hours of video uploads every minute, requiring a delicate balance between compression speed and quality. As a result, YouTube automatically compresses high-definition videos into lower-resolution versions. However, YouTube allows users to upload various types of content, as long as they do not violate content guidelines. Our proposed method capitalizes on this fact by disguising visual content as seemingly meaningless data, which typically goes undetected by content filters.

6.3.1 Related Works and Compression Techniques

Steganography and reversible data hiding in encrypted images are established techniques for secure content transmission (Shih, 2017; Qin & Zhang, 2015; Zhang, 2011; He,

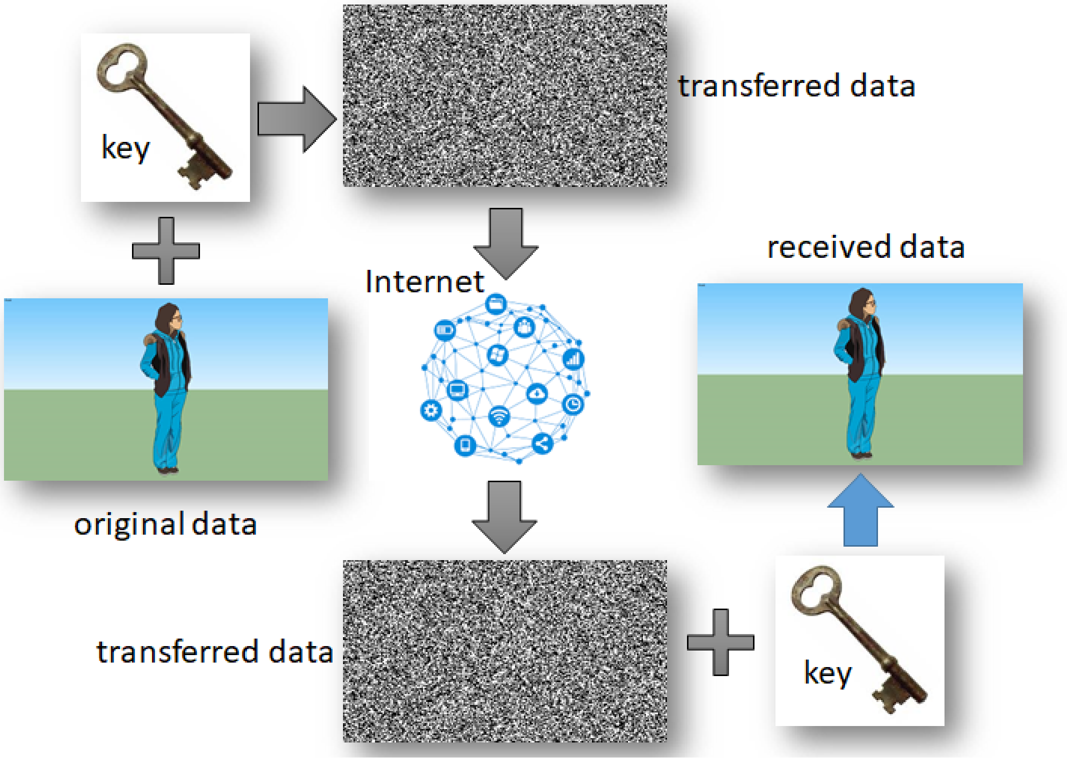


Figure 6.2: Diagram displays our proposed system

Chen, Luo, Tang & Huang, 2018). These methods work well with different types of image and video compressions such as JPEG and H.264/MPEG-4, albeit with limitations like lossy compression affecting the hidden data. For example, high-compression JPEG retains only about 5% of the original bits (Lin & Chang, 2001).

Compression methods like JPEG, H.264, and MPEG4 are prevalent in today's multimedia content (Wallace, 1992; Wiegand, Sullivan, Bjontegaard & Luthra, 2003; Perkins & Hodson, 2003). JPEG is commonly used for images due to its balance between quality and compression. H.264 and MPEG4 offer higher video compression rates by eliminating redundant information.

In our evaluation, we focus on JPEG compression to assess the efficacy of our encoding and decoding techniques.

6.3.2 Problems - the facing issues

Why is it not straight-forward to do such image hiding scheme? An image contains a large number of pixels $I(i,j)$ with $i \in (1,2,3,...,W)$ and $j \in (1,2,3,...,H)$; W, H are the width and the height the image I. Assume it is a monochrome image, e.g. $I(i,j)$ is one integer. If the image is colour, each $I(i,j)$ is an array of three colour: red, green, and blue. The most obvious way to encrypt a monochrome image is to multiply every pixel of the image with one reversible function $F(x, Key)$:

$$I'(i,j) = I(i,j) \times F(x, Key) \tag{6.1}$$

And in order to get back the original image, we only need to multiply the encrypted image with the inverse function of $F(x, Key)$:

$$I(i,j) = I'(i,j) \times (F(x, Key))^{-1} \tag{6.2}$$

Here, there are some issues that we have to face. First, the function $F(x, Key)$ must not be linear, and it must be complex enough to make the original visual content of the image not visible. Two pixels with similar colour/intensity should not appear to be similar in the encrypted image, e.g. the mapping of intensity $1 \longleftrightarrow 175$, $2 \longleftrightarrow 25$, and $3 \longleftrightarrow 167$, for instance. We must have a complex enough reversible function $F(x, Key)$ where a Key can be combined to prevent the leakage of the original data. On the other hand, the function $F(x, Key)$ must also be simple so that the complexity of the process is not considerable; we have to multiply every single pixel with such function, we need a fast running process. A lookup table can be implemented to serve this purpose. Alternatively, one easy way to do that is to Exclusive Or (XOR) the original image with one generated random-dot image with the same size; the random dot image will be the key to unlock the content. The encrypted image will appear mostly

Table 6.1: Number of inaccurately pixels on .PNG and .JPG random dot images after compression

Intensity Difference	PNG	JPG100	JPG95	JPG90	JPG80
1 value	0%	9.3%	79%	89%	95%
5 values	0%	0%	2.2%	24%	54%
10 values	0%	0%	0%	1.6%	21%

random.

The random-dot way of encryption has a serious issue with lossy compression. The property of random dot image is that, adjacent pixels are very likely to be different from each other. Image compression such as JPEG will not be able to retain the values of all the pixels after a compression, even with Quality Factor of 100.

In fact, we have tested the quality of random dot JPEG images versus lossless PNG images. We evaluated the performance of four levels of compression: 100, 95, 90, and 80. The results are shown in Table 6.1.

On average, 9.3% of the pixels (at one level of intensity) are altered after a JPEG compression with a Quality Factor of 100. As the Quality Factor of the compression decreases to lower levels, such as 80, over 95% of the image will be changed at the pixel level.

The Exclusive Or (XOR or $\oplus$) function is not robust enough for use in lossy compression either. Although XOR has the commutative property, which is widely used in Computer Science:

$$Data \oplus Key = Locked \tag{6.3}$$

and

$$Locked \oplus Key = Data \tag{6.4}$$

if the locked data is slightly changed, it is not guaranteed that the decoded data will only be slightly changed. There are cases where $A \oplus K = B$ but $(A + 1) \oplus K \neq (B + 1)$.

For example, if the original data is 213 and the key is 170, we have:

$$213 \oplus 170 = 127$$

The encrypted data is 170, which can be transferred over the network. However, if the data is manipulated, such as increased to 128 when decrypted, we get:

$$128 \oplus 170 = 42$$

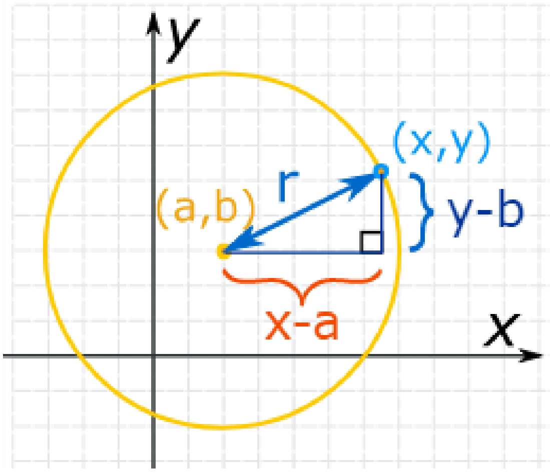
There is a significant difference between 42 and 170. Therefore, XOR is not completely suitable for image encryption and decryption, and we need to find a more robust approach.

6.3.3 Design and Implementation

We need to build a reversible function $F(x, Key)$ that is capable to encode an image I and a secured key Key, and it can generate a random-looking pattern I' which is robust for lossy compression. On other words, it needs a property: $I_x \times F(x, Key) = A$ but $(I_x + 1) \times F(x, Key) \neq A + 1$; with I_x is an arbitrary intensity. However, two adjacent pixels I_x and I_{x+1}, which have the same intensity/colour ($I_x = I_{x+1}$) should appear differently in the encrypted image, e.g. $I'_x \neq I'_{x+1}$ so that the hidden content is not visible. After encryption, the intensity distance k between the two adjacent pixels (same intensity originally) is calculated as:

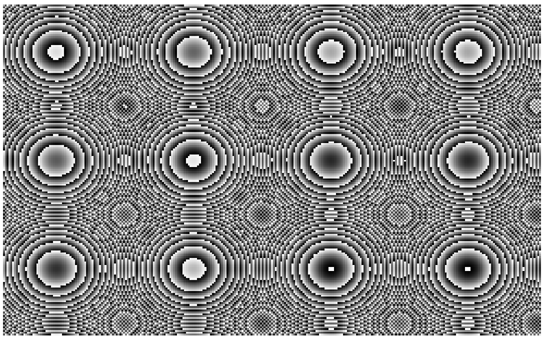
$$|I'(x) - I'(x+1)| = k; k \neq 0$$

This value of k should not be zero, but it should not be too large either, at least in one direction (x or y) so that the lossy compression does not significantly affect the changes in intensity.



(a) Equation of a circle

(b) Water waves with circular ripples from the rain



(c) Our proposed random circular patterns

Figure 6.3: Motivation and our proposed random patterns

Motivated by the water waves with circular ripples from the rain as seen in Fig. **??**. The patterns of them look half random, the intensities of the circles with the same centre are the same. From the standard form of a circle equation, we have:

$$(x - a)^2 + (y - b)^2 = r^2 \tag{6.5}$$

There are a number of parameters: a, b, r, which can be used to modify the shape of the circle. These could be used as keys to unlock the image encryption of our system.

Encoding of the Circular Pattern with Keys

Based on the formula 6.5, we propose a encoding process to build a circular pattern from any image. For each pixel, we calculate its encoded form as:

$$I'(i,j) = k_1 \times ((k_2 \times i - k_3)^2 + (k_4 \times j - k_5)^2) - I(i,j) \tag{6.6}$$

Here, $I(i,j)$ is a pixel of original image, $I'(i,j)$ is the encrypted image, and the set of keys $k_{1..5}$ are the keys to lock and unlock the image. If each key is a three digits number, to unlock it correctly, we need a set of $3 \times 5 = 15$ correct digits. The chance of brute forcing it will be $1/10^{15}$, which is almost zero.

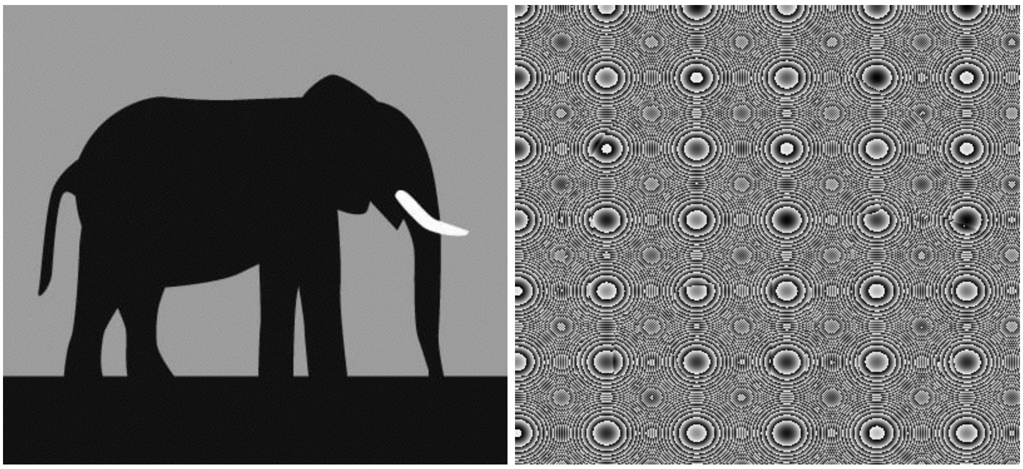


Figure 6.4: Encode image of an elephant picture

Fig. 6.4 displays an example of our encoding result using the equation in formula 6.6. This image is simple, but it is, in fact, a hard image to hide because it has a very high contrast boundary and uniform colours. If we mask this image with another arbitrary image, the boundary of the elephant is straightforward to distinguish by human eyes. With our proposed method, it is not possible for anyone to say that the elephant is hidden underneath.

Decoding of the Circular Pattern with Keys

We have made so that the decoding the circular pattern is simple and straight forward. Each pixel is decoded by:

$$I(i,j) = k_1 \times ((k_2 \times i - k_3)^2 + (k_4 \times j - k_5)^2) - I'(i,j) \tag{6.7}$$

Notice that, instead of using XOR, we just use simple subtraction function (minus) with unsigned 8-bit integer. The unsigned integer has the property: $K - A = B$ and $K - B = A$. The results will always be positive due to Binary Overflow (Brown, 1999). This property ensures that the encoded image output is always valid to display.

Contrast Compression of Original Image to Prevent Invalid Overflow after Compression

The formula 6.6 and 6.7 above will help create and return the correct input and output; if and only if the image is going through a lossless compression. However, this is not a valid assumption; lossy compression (e.g. JPEG) will be applied. As seen in Fig. 6.5, it is likely that many pixels will be manipulated for achieving good compression. The amount of manipulation is unknown, and it could be 10 to 20 values of intensity changed.

This unavoidable manipulation could affect badly on the decoded results, especially on the maximum and minimum spectrum of the intensity. E.g. $I'(x,y) = 5$, is decoded to $I(x,y) = 252$; but after compression, $I'(x,y) = 5$ is changed to $I'(x,y) = 5 + 10 = 15$ and get decoded to $I(x,y) = 252 + 10 = 7$ after overflow. Thus, the pixel turns from white to black; and vice-versa. Overflow of binary will create a large number of black dots on white backgrounds, and white dots on black backgrounds.

To minimise this overflow of intensity; we have to stretch the two upper and lower spectrum of the image intensity. The stretch should be less than 10% of the 256 levels

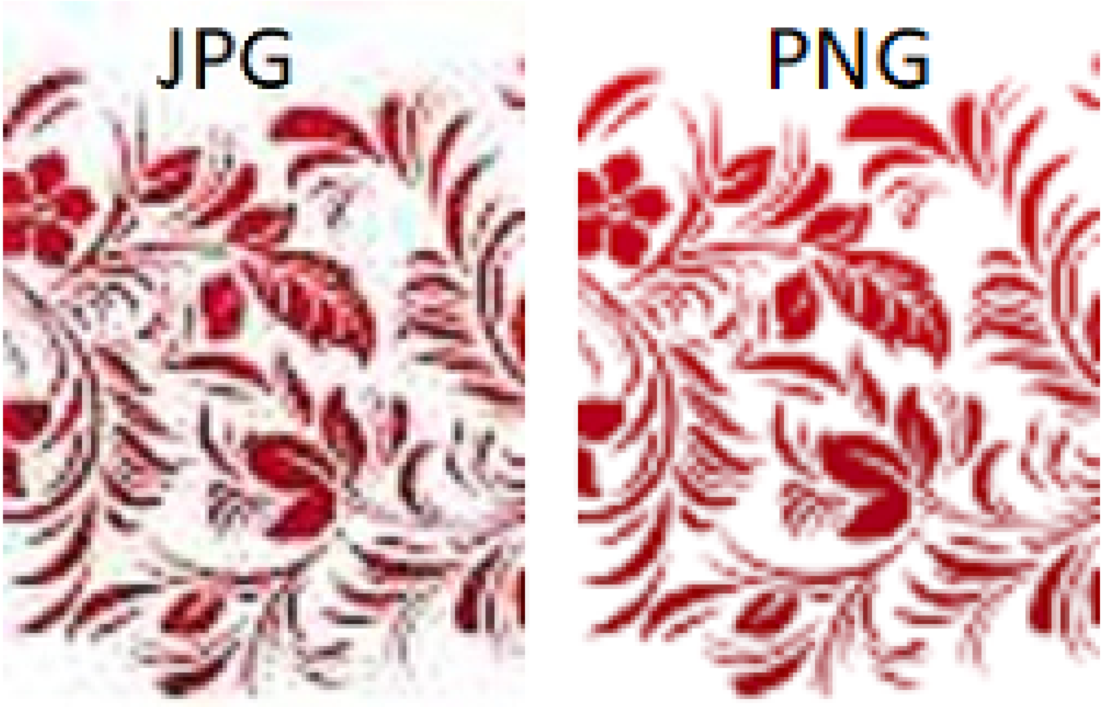


Figure 6.5: Visual lossy JPEG vs. lossless PNG comparison

of intensity range, the formula is below:

$$J(i,j) = (\alpha - \beta) \times \frac{I(i,j)}{255.0} + \beta \tag{6.8}$$

This stretch makes the minimum intensity value of pixels to be $\beta > 0$, and the maximum value is $\alpha < 255$. Stretching before encoding will significantly reduce the intensity overflow effect discussed above.

After decoding with the key, we have to de-stretch the intensity to get the original form of image, using the below formula:

$$I(i,j) = 255.0 \times \frac{(J(i,j) - \beta)}{\alpha - \beta} \tag{6.9}$$

Fast Implementation

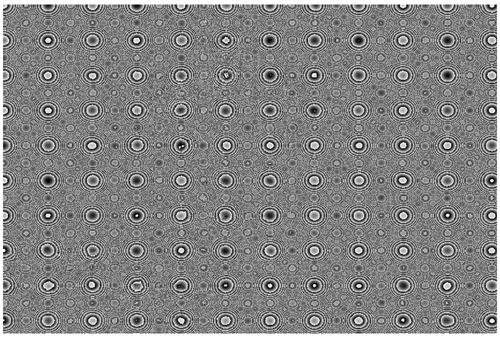
Originally with the formula 6.6 and 6.7, each pixel of the encoded image is created by multiplying itself with function $F(x, Key)$. To do that, it will take the complexity of at least $O(n) \times T$ where n is the number of pixels. Tested in our system, each frame take up-to three seconds to process due to the individual pixel-based manipulation. To make it faster, and reduce the complexity to $O(1) \times T$, we proposed that the lock image is created first, and it is created once only:

$$I_{locked} = k_1 \times ((k_2 \times i - k_3)^2 + (k_4 \times j - k_5)^2) \tag{6.10}$$

Then, the encode and decode of the image can be done by direct image subtraction: $I' = I_{locked} - I$ and $I = I_{locked} - I'$, respectively. The processing time is reduced dramatically, and actual quantitative figures will be shown and discussed in the next section.

6.3.4 Results and Evaluations

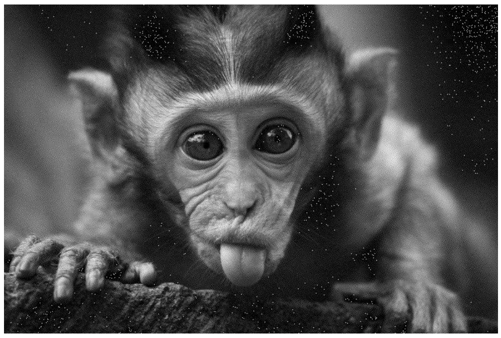
Fig. 6.6 show some examples of our encoded image and three decode images after the encoded image is saved to different levels of JPEG compression. We applied the same stretch level of 10%. It shows that with the JPEG compression quality 75 or more, the decoded image looks almost the same as the original. The quality reduces when the compression quality is at 60, and at level 30, there are many noisy dots presented. However, the majority of pixels are maintained to depict the monkey in the picture. Even with the Quality of 01, the majority of the image is still visible to naked human eyes.



(a) Encoded pattern

(b) Decoded from JPEG image with Quality 90

(c) Decoded from JPEG image with Quality 75



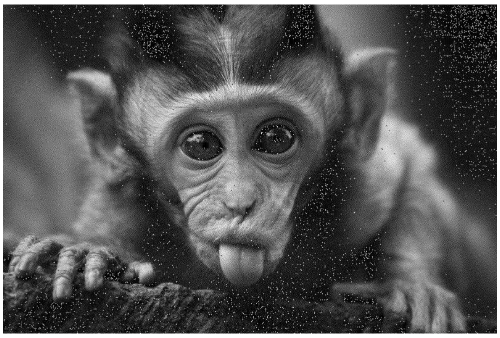
(d) Decoded from JPEG image with Quality 60

Figure 6.6: Encoded pattern and three decoded results with stretch level 10%

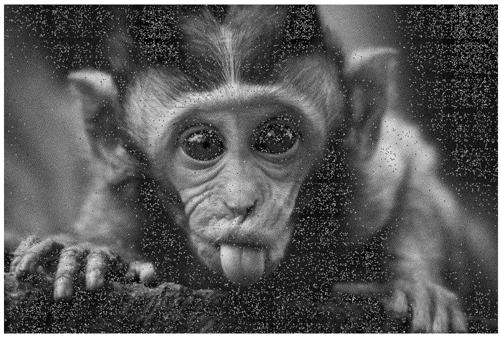
Quality of Images after Decoding

To evaluate the results quantitatively, we carry out a number of experiments. We select images with different contents and sizes. We encode them with a set of secured keys. We save the encoded image using JPEG compression with various quality level: 100, 90, 80, ... 10. We reload the images, and start decoding with the same set of keys. We then compare the decoded images with the original images. Pixels within 1, 5, 10 levels of intensity are collected to find out the accuracy of the encode decode at different levels. The results are collected and displayed in Tab. 6.3.

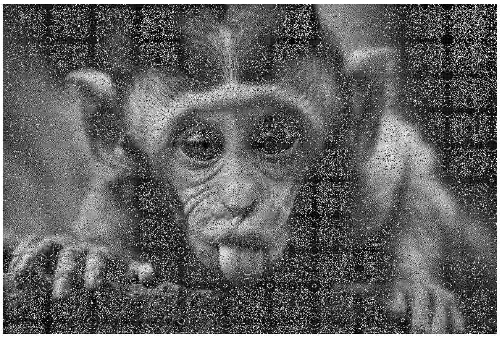
As seen, our encode/decode approach could not maintain the image accurately at one value different. It is evident because JPEG compression will most likely to change the value of the individual pixels anyway. However, our approach is very robust at 5 and 10 different intensity level. At JPEG90, more than 99% of the image are decoded correctly



(a) Decoded from JPEG image with Quality 45



(b) Decoded from JPEG image with Quality 30



(c) Decoded from JPEG image with Quality 15

Figure 6.7: Other decoded results with stretch level 10%

Table 6.2: Number of inaccurately decrypted pixels on PNG and lossy JPG images

Difference	JPG100	JPG90	JPG80	JPG60	JPG40	JPG20
1 values	20.7%	73.8%	85.6%	91.9%	94.4%	96.3%
5 values	0%	5.08%	29.6%	56.4%	68.4%	78.9%
10 values	0%	0.10%	4.12%	25.7%	42.2%	59.6%

within ten values of intensity difference. Within 5 values, our approach achieves 95% accuracy. One other word, our encode/decode approach, is capable of maintaining the majority of the image quality and should be suitable for further image processing.

Processing Speed of Encoding and Decoding

As stated above, we have built a fast implementation of the proposed method. We test the performance by running encoding and decoding on a general machine with a general specification. It is a no-dedicated GPU system - a Desktop machine with Intel Core i5-6500 processor @ 3.2 GHz and 16.00 GB of RAM, running Windows 10 operating system and Python 3.4.

Table 6.3: Speed of Encoding

Size	(500x500)	(1000x1000)	(1500x1500)	(2000x2000)
Speed	73.8 fps	48.7 fps	22.8 fps	11.2 fps

We resize images into four sizes: (500×500), (1000×1000), (1500×1500), (2000×2000). We run each with the encode and decode process ten times. The average time is then calculated to how many frames per second. The final results are shown in Tab. 6.3 and Tab. 6.4.

Table 6.4: Speed of Decoding

Size	(500x500)	(1000x1000)	(1500x1500)	(2000x2000)
Speed	266 fps	61.6 fps	26.3 fps	15.2 fps

Both the tables show that our encode and decode process could run at relatively high speed. At the size of (1500×1500) or less, it is capable to run in real-time, e.g. approx. 24 FPS.

6.4 Chapter Summary

Manual verification by a third party is crucial for ensuring the accuracy of fall detection systems. However, it also introduces the challenge of preserving the privacy of the individual concerned. This chapter addresses this dilemma by proposing two methods: skeletal pose imaging and visual encryption. Both approaches aim to strike a balance between the need for manual verification and the imperative of maintaining privacy.

Chapter 7

Conclusion

7.1 Thesis Summary and Contributions

This thesis journeys through the intricate challenges at the crossroads of healthcare and the Internet of Things (IoT), focusing primarily on pioneering approaches to fall detection and data privacy. The inaugural chapter establishes the compelling need for secure, efficient fall detection mechanisms within the scope of healthcare IoT, serving as the research impetus for the ensuing chapters.

Chapter 2 serves as a literature review, offering a panoramic view of the existing scholarship in IoT healthcare. It delves into foundational technologies and theories, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), thereby setting the stage for the methodologies and algorithms developed in subsequent chapters.

Chapter 3 elucidates the research design and methods implemented. It introduces the novel Falls Management Framework (FMF), a system integrating both wearable and ambient sensors to deliver a synergistic fall detection solution. Leveraging machine learning techniques like SVM, k-NN, and Naive Bayes, FMF can differentiate falls from everyday activities with high accuracy. Data from accelerometers is processed in real-time using pattern recognition algorithms. The Adaptive Context-aware Fall Detection Algorithm (ACFDA) undergoes rigorous evaluation, employing datasets from various devices such as Nexus 4 and Nubia NX511j smartphones, to ensure minimal false positives and negatives.

Chapter 4 explores cutting-edge features from extant systems like SmartFall and FallRisk. It leverages depth sensors like Microsoft Kinect to add another layer of precision. This chapter validates the model's proficiency in classifying a multitude of human activities across diverse age groups by evaluating it against the comprehensive SysFall dataset.

In Chapter 5, we shift focus to a more advanced, Visual Object-based Fall Detection Algorithm that relies on environmental sensors and video footage, circumventing the limitations of wearable sensors. The algorithm operates on four core modules: Video Capture and Playback, Pose Landmark Detection, Fall Recognition, and User Interface Interactivity. The system utilizes the MediaPipe library and emphasizes the vertical distance between the nose and hip landmarks to ascertain falls. Rigorously tested on the SysFall dataset, it claims high accuracy rates and is especially suited for monitoring vulnerable populations like the elderly. A user-friendly Graphical User Interface (GUI) enhances accessibility and ease of use.

Finally, Chapter 6 underscores the criticality of minimizing false detections and introduces two privacy-conscious methods for manual fall verification: skeletal pose imaging and visual encryption. These techniques strike a balance between robust fall detection and individual privacy, incorporating image encryption methods like steganography and reversible data hiding for added security layers.

7.2 Future Work

As promising as the contributions of this thesis are, there exist several avenues for future research and development. First, while the Falls Management Framework (FMF) and the Adaptive Context-aware Fall Detection Algorithm (ACFDA) have shown impressive results, further tuning of their machine learning models could improve accuracy and reduce computational overhead. Exploration into ensemble methods or deep learning architectures may offer avenues for even more robust fall detection algorithms.

Second, the Visual Object-based Fall Detection Algorithm warrants further study. In particular, real-world validation through extended field tests would be invaluable for confirming its practical utility. Additional algorithms could be incorporated to handle a broader range of scenarios, including low-light conditions and occlusions, which are typical challenges in practical deployments.

Third, the aspect of data privacy, although addressed, requires a more comprehensive approach. Future work could involve the development of end-to-end encryption protocols that seamlessly integrate with the existing systems without compromising user experience. Special attention should be given to the practical implementation of the privacy-preserving methods like skeletal pose imaging and visual encryption.

Fourth, our solutions are particularly geared towards the elderly; however, fall detection is a concern for other vulnerable populations as well. Future iterations could adapt the framework for use among children, athletes, or industrial workers, who also stand to benefit from reliable fall detection mechanisms.

Fifth, while we have extensively tested our algorithms on the SysFall dataset, other publicly available datasets or even proprietary datasets could be used to further validate the generalizability of our methods.

In sum, future work should strive for a seamless, secure, and inclusive ecosystem that further refines the balance between high-accuracy fall detection and preservation of user privacy.

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